An Econometric Analysis of the Economic and Environmental Efficiency of Dairy Farms in the KwaZulu-Natal Midlands

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DECLARATION

By submitting this dissertation electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the authorship owner thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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Abstract

This dissertation is an analysis of dairy production in the Midlands district of KwaZulu-Natal. The analysis of agricultural production generally ignores undesirable outputs that are produced alongside desirable outputs. This research attempted to integrate a model of nitrate leaching from dairy production into a multiple input/output representation of the production technology, together with the analysis of technical efficiency. Estimation of both technical efficiency and environmental efficiency were done following the parametric econometric stochastic frontier (SFA) and the nonparametric mathematical programming data envelopment analysis (DEA) approaches.

The study used unbalanced panel data from 37 individual highly specialized dairy farms for the period 2000 to 2007 and totals to 2130 observations. Production functions for the three outputs; milk, animals and farm produced feed, were fitted as a simultaneous system to model the farms' production activities for the econometric SFA estimation of technical efficiency. A single equation reduced form was fitted as a frontier to allow for the estimation of the relative efficiencies of the individual farms. The results showed that with data this detailed it was possible to refine the model until it fits very tightly. Indeed, in the gross output model that includes cows, there was nothing left to call inefficiency and what was clearly a frontier becomes a mean response function. Technical efficiency was further calculated using the nonparametric DEA approach using the same dataset.

The estimation of environmental efficiency was done using both SFA and DEA approaches. Undesirable emissions of nitrate were represented within the models by calculating nitrogen surplus (kg/ha) for each farm. This nitrogen surplus value was based on the intensity of the use of nitrogen containing inputs and the nitrogen content of marketable products specific information and from farm data which were used to calculate a farm nitrogen balance. The stochastic estimation of environmental efficiency used the same data that were used for the estimation of technical efficiency. However, for the DEA calculation of environmental efficiency, a balanced cross-section dataset for 34 farms participating in a pasture-utilization programme was used. This dataset was used because it had quantities of nitrogen fertilizer and other nitrogen containing inputs.

Results indicate that there was minimal “over-usage” (over production) of milk thus reducing milk output alone will not lead to improved environmental efficiency. Farm size, herd size, and quantity of nitrogen fertilizer applied, present the best scope of reducing nitrogen surplus thus improving environmental efficiency of the dairy farms. Reducing imported feed by relying more on home grown feed can also help reduce nitrogen surplus. This is feasible because dairy farmers in the KwaZulu-Natal Midlands can produce most of the feed on farm.

In summary, to obtain environmental efficiency milk production would have to be reduced by 80 litres per hectare; farm size by 73.69 ha; herd size by 33 cows, nitrogen fertilizer application by 74.3 kilograms per hectare; and imported feed by 13.4 kilograms of dry matter per hectare. The adjustments that would be required if environmentally inefficient farms were to adopt best practice technology and move towards their environmental production frontiers indicate that the production of pollutants (nitrogen surplus) could be reduced at negligible cost to milk production. The positive correlation between technical and environmental efficiencies indicates that improving environmental efficiency could be associated with improvements in technical efficiency. Thus, policies aimed at improving both efficiencies could have substantial rewards.

Uittreksel

In hierdie tesis word suiwelproduksie in die Middellande van KwaZulu-Natal van nader beskou. Met die ontleding van landbouproduksie, word ongewenste uitsette wat saam met gewenste uitsette geproduseer word, gewoonlik oor die hoof gesien. Hierdie navorsing poog om ’n model van nitraatvrylating uit suiwelproduksie in ’n veelvuldige inset/uitset verteenwoordiging van die produksietegnologie, te integreer by die analise van tegniese doeltreffendheid. In opvolging van die benaderings tot die parametriese ekonometriese stogastiese front (SFA) en die omvattingsanalise ten opsigte van die nie-parametriese matematiese programmeringsdata, is beramings van sowel tegniese as omgewings doeltreffendheid gedoen.

In die studie is gebruik gemaak van paneeldata van 37 individuele hoogs gespesialiseerde melkplase vir die tydperk 2000 tot 2007, wat altesaam 2130 waarnemings beloop. Produksiewerksaamhede vir die drie uitsette; melkproduksie en diere- en plaasgeproduseerde voer, is as ’n gelyklopende stelsel ingepas om die plase se produksiewerksaamhede vir die ekonometriese SFA-beramings van tegniese doeltreffendheid weer te gee. ’n Enkele vorm om gelykmaking te verminder is daargestel as ’n front vir die beraming van die relatiewe doeltreffendhede van die individuele plase. Die resultate het bewys dat data van hierdie omvang dit moontlik maak om die model sodanig te verfyn dat dit net-net inpas. By die bruto uitset-model waarby koeie ingesluit is, was daar inderdaad niks wat op ondoeltreffendheid gedui het nie en wat eers ’n duidelike front was, het ’n betekenisvolle responsfunksie geword. Voorts is tegniese doeltreffendheid bereken deur aanwending van die nie-parametriese DEA-benadering, deur gebruik te maak van dieselfde datastel.

Die beraming van omgewingsdoeltreffendheid is gedoen deur gebruikmaking van sowel SFA- as DEA-benaderings. Ongewenste nitraatvrylatings is in die modelle gevind deur die stikstofsurplus vir elke plaas te bereken (kg/ha) Die waarde van hierdie stikstofsurplus is gebaseer op die intensiteit van die gebruik van stikstofbevattende insette en bepaalde inligting oor die stikstof-inhoud van bemarkbare produkte, sowel as van plaas data, wat gebruik is om ’n stikstofbalans vir die plaas te bereken. Dieselfde data wat aangewend is vir die beraming van tegniese doeltreffendheid, is gebruik om die stogastiese beraming van omgewingsdoeltreffendheid te bepaal. Vir die DEA-berekening van omgewings-

doeltreffendheid, is egter ’n gebalanseerde kruisseksie datastel gebruik vir 34 plase wat aan ’n weidingsbenuttings-program deelgeneem het. Die bepaalde datastel is gebruik omdat dit dosisse stikstofbemestingstof en ander stikstofbevattende insette bevat het.

Resultate het op minimale “oorgebruik” (oorproduksie) van melk gedui en daarom sal die vermindering van slegs die melkuitset nie lei tot verbeterde omgewingsdoeltreffendheid nie. Plaasgrootte, kuddegrootte en die dosis stikstof wat toegedien is, verskaf die beste beeld van verminderde stikstofsurplus, wat dus tot verbeterde omgewingsdoeltreffendheid op melkplase lei. Die vermindering van ingevoerde voer deur meer op plaasgeproduseerde voer staat te maak, kan ook meewerk om stikstofsurplus te laat daal. Dit kan gedoen word omdat melkboere in die Middellande van KwaZulu-Natal die meeste van die voer op die plaas kan produseer.

Ter samevatting kan gesê word dat om omgewingsdoeltreffendheid te bereik moet melkproduksie met 80 liter per hektaar verminder word, plaasgrootte met 73.69 ha, kuddegrootte met 33 koeie, stikstofbemestingtoediening met 74.3 kilogram per hektaar en ingevoerde voer met 13.4 kilogram droë materiaal per hektaar. Die aanpassings wat nodig sal wees indien omgewingsdoeltreffende plase beste praktyk-tegnologie sou aanvaar en sou aanbeweeg na hulle omgewingsproduksiefronte, dui daarop dat die produksie van besoedelende stowwe (stikstofsurplus) verminder kan word teen geringe koste aan melkproduksie. Die positiewe verband tussen tegniese en omgewingsdoeltreffendhede, dui daarop dat die verbetering van omgewingsdoeltreffendheid, in verband gebring kan word met verbeterings in tegniese doeltreffendheid. Beleid wat op verbetering van beide doeltreffendhede gemik is, kan daarom aanmerklike voordele inhou.

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To God be the glory!

Chapter 1: Introduction

1.1 The South African dairy industry

The dairy industry is the fourth largest agricultural industry in South Africa, representing 5.6% of the gross value of all agricultural production (WESGRO, 2004). During the 2000/2001 season, the primary dairy industry was one of the fastest growing agricultural sectors in South Africa, growing by 16.6% compared to a decline in gross income of 8.7% in the red meat industry (Coetzee, 2002). The gross value of milk produced during the 2002/03 production season (March-February), including milk that was produced for own consumption on farms, was estimated at R3 862 million (Department of Agriculture, 2003:54). However, the retail value of the total dairy industry is estimated at around R7 billion annually. More than 65% of dairy products are distributed through hypermarkets, supermarkets and superettes (WESGRO, 2004).

Many agricultural products in South Africa have gone full circle from absolute control to a free market, and the dairy supply chain is no exception. The dairy supply chain was historically controlled and regulated by means of the Dairy Industry Control Act of 1961, the Marketing Act of 1968, various Dairy and Milk Boards, national, provincial and local health legislation, plus a variety of other acts and regulations. A surfeit of control measures were in place that regulated the South African dairy supply chain. The plethora of control measures included, amongst others, health issues in production and processing of raw milk and the fixing of margins during the different processing phases until it landed as an end product with fixed prices or fixed margins in the retail outlets (NAMC, 2001). Only the more dramatic changes will be highlighted here as these will put the structural changes in the dairy supply chain affecting its costs and the end price into perspective.

In 1971 Government allowed margarine to be coloured yellow. This resulted in a drop in annual butter sales from more than 54000 tons in 1971 to 16000 tons in 1979 (NAMC, 2001:22), and changed the face of the industry. The Dairy Industry Control Act was abolished in 1987. The final deregulation steps followed during the Uruguay Round of the General Agreement on Tariffs and Trade in 1994 when quantitative import control was replaced by import levies. This had the important effect of increasing legal and illegal imports (NAMC, 2001: 26-27).

The total number of fresh milk producers in South Africa declined from 3899 in January 2007 to 3332 in March 2010 (MPO, 2010). The number of producers per province is shown in Table 2. Since 1997, the number of dairy farms has decreased by 53 percent. The biggest decrease in dairy farms occurred in the Northern Cape (67%) and the Free State had a decrease of 30 percent (MPO, 2010). The trend towards the concentration of dairy production in the pasture-based areas along the coast continued.

Interestingly, production of milk per producer increased on average (MPO, 2003; Coetzee, 2002). Although production per producer increased, costs of production also increased (by an average 44 percent from 2001 to 2003 (MPO, 2003)). For the majority of dairy farmers in KwaZulu-Natal, the highest cost items in milk production are feed and labour (Coetzee, 2002; Gordijn, 1985). The efficient use of all factors of production will result in efficient production and profit maximization. However, even a small reduction in feed and labour cost would result in significant improvement in the profitability of dairy farms in KwaZulu-Natal (Coetzee, 2002).

There has been a clear movement of milk production from the inland to the coastal (KwaZulu-Natal, Western Cape and Eastern Cape) areas in the country. Milk production in the coastal areas increased from 52% to 62% of the total between 1995 and 2000. There are a number of possible reasons for this spatial concentration of dairy farms along the coastal areas of South Africa. One reason is that these coastal areas are within close proximity to viable ports and this tends to lower transportation costs of imported inputs relative to more inland areas. Another reason could be that the coastal areas are more suitable because of mild temperatures and good rainfall and these climatic factors assure good-quality natural and cultivated pastures (Department of Agriculture, 2003:54). Unfortunately the major market for dairy products lies in the inland areas (Coetzee, 2002).

Although the variable cost of producing milk from pastures in the coastal areas is lower, the extra cost to transport milk from coastal areas to the markets should be taken into account. Despite the fact that variable cost of producing milk from pastures is lower in the coastal areas, there are still dairy farmers that are less efficient in their milk production, and are thus struggling to break even. It is this dichotomy in production efficiency in the KwaZulu-Natal dairy industry that is of particular interest and begs research to establish the determinants of technical, economic, and environmental efficiencies. The number of smaller milk producers is declining while the share of larger producers in the total milk production is growing. The average milk producer now produces 17.3 litres per cow per day (MPO, 2010).

Declining real (inflation-corrected) farm-gate returns for milk are an ongoing challenge to dairy farm business viability. Returns, generally, are declining in the industry as inflation increases the cost of farm inputs, new technology reduces the cost of production of substitutes and competition provides consumers access to better value or substitute products from other farmers (MPO, 2004).

The dairy farmer is currently caught in a price-cost squeeze (effect of lower real output prices and increased costs). As a result, it is imperative that the farmer be familiar with the expenses associated with the farming business in order to remain viable. Other industries can set the selling price of their commodity, yet in the dairy industry the only means of increasing profits in the short-run is to maintain production and reduce input costs (MPO, 2003; Gordijn, 1985). Although the dairy marketing board was abolished years ago, farmers supplying their milk to processors still operate under some sort of quota system in that they enter into a contract with the processor to supply a given quantity and quality (butterfat content) of milk.[1] Failure on the farmer's part to meet contractual obligations incurs penalties from the buyer in the form of lower buying price per litre. The survival of the dairy farmer therefore hinges on the farmer becoming cost efficient and having more business acumen which requires technical efficiency.

1.2 Introducing production function and technical efficiency concepts

The basic definition of a production function is the maximum output that can be produced with a given input combination for a particular technology, thus technology is the basic element of a production function. Kumbhakar and Lovell (2000:25-26) define a production function or frontier as a representation of maximum output that can be obtained from any given input vector or, alternatively, the minimum input usage required to produce any given output vector. The detail and accuracy of a production function depends on its use. These matters will be further developed in Chapter 2.

Technical efficiency is a measure of the ability of a firm to avoid waste, either by producing as much output as technology and input usage allow (output-maximization) or by using as little input as required by technology and output production (input-minimization). Therefore, the analysis of technical efficiency can have an output augmenting orientation or an input conserving orientation. Koopmans (1951) formally defined technical efficiency by stating that a producer is technically inefficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Thus a technically inefficient producer could produce the same

[1] This suggests that cost minimisation subject to an output constraint is the appropriate way to model dairying. See the discussion in the next section.

outputs with less of at least one input, or could use the same inputs to produce more of at least one output.

Following Koopmans (1951) definition, Debreu (1951) and Farrell (1957) introduced a measure of technical efficiency. With an input conserving (minimizing) orientation their measure is defined as the maximum equi-proportionate (often referred to as radial) reduction in all inputs that is feasible with given technology and outputs. The measure of technical efficiency devised by Debreu (1951) and Farrell (1957) will be referred to as the Debreu-Farrell measure in this chapter for brevity. With an output augmenting (maximization) orientation their measure is defined as the maximum radial expansion in all outputs that is feasible with given technology and inputs. In both orientations a value of unity indicates technical efficiency because no radial adjustment is feasible, and a value different from unity indicates the severity of technical inefficiency.

1.3 Introducing the concept of environmental efficiency

Until the turn of the twentieth century, agriculture in South Africa could be viewed as being environmentally friendly, with the limits on production dependent on the natural resource endowment, the regenerative processes of the soil to replenish itself, and on the cycling of crop and animal wastes in a closed, ecologically sustainable system. However, during the twentieth century agriculture experienced a complete evolution, becoming a much more intensive economic activity that relies heavily on external inputs such as fertilisers, pesticides, machinery and energy. This intensification has allowed the production of larger quantities of output from relatively smaller areas. The amelioration of soil fertility deficiencies with fertilisers increases crop yields and allows for increases in the stocking rate of grazing animals, for example. Unfortunately, this change has resulted in the loss of the ecological balance, and farming systems becoming more unsustainable with the concomitant potential for leakage of environmentally detrimental substances out of that system. This dissertation is concerned with measurement of the efficiency of controlling for such leakage while also measuring the economic efficiency of the production system.

For a long time, the main objective of South African commercial agricultural policy has been to increase agricultural productivity, with the result that productivity has been steadily increasing (Thirtle *et al.*, 1993). Technological development enables the substitution of variable inputs (fertiliser, feed and pesticides) for labour (Rutten, 1992). This increased use of variable inputs has led to environmental side effects, which are becoming more and more apparent (Vink, 2004). The result has been that contemporary policy with respect to agriculture has changed into a set of broader objectives, namely efficiency, equity and sustainability. In the dairy sector of South Africa the focus has to be mainly on environmental pollution due to excess application of nutrients. For instance acid rain is related to emission of ammonia, nitrates are found in drinking water, and phosphate is found in surface water. These environmentally detrimental effects are all related to excess fertilisation (nitrogen and phosphorus).

1.4 Defining the empirical problem of measuring environmental efficiency

In line with traditional policy on agriculture, the technical and economic efficiency of dairy farms internationally has been researched intensively. This provides valuable measures for evaluating the productive performance of farms in the context of production possibilities and cost minimisation. With the increasing consciousness about the environmental problems caused by agriculture and newly formulated policies, the environmental performance of farms has become increasingly important (Färe *et al.*, 1996). At present, the supply of quantitative information about agri-environmental linkages is inadequate. Without such information, governments and other users cannot adequately identify, prioritise and measure the environmental impacts associated with agriculture, which makes it difficult to improve the targeting of agricultural and environmental programmes and to monitor and assess policies (OECD, 1997:3). Nutrient balances are available as indicators for agricultural nutrient use (OECD, 1997:25). Although indicators may be available for both the economic and environmental objectives of the government, a comprehensive performance measure that combines economic and environmental performance is yet to be developed.

The standard efficiency methodology is an attractive framework to analyse the (comprehensive) environmental performance of (dairy) farms. Efficiency scores are performance measures on the basis of which production units are evaluated. In efficiency measurement, observations are compared with optimal production conditional on inputs (or outputs, depending on the definition used). Efficiency scores readily show the potential improvements. Technical efficiency measures do not need price information nor do they require the specification of any a priori weight on the environmental impacts that are being aggregated (Tyteca, 1996). Another advantage of efficiency methodology is that it fits in with the expression 'environmental efficiency' or 'eco-efficiency' that is frequently used in policy reports. One of the challenges for South African agriculture is to improve efficiency in production and farm processes in order to optimise inputs and emissions. Environmental efficiency has so far not been estimated either following econometrically (parametric) models or mathematical programming (nonparametric) approaches in South Africa, specifically in the agricultural sector.

The basis of standard efficiency methodology was developed by Farrell (1957). He proposed that the efficiency of a firm consists of two components: (i) technical efficiency, which reflects the ability of a firm to obtain maximum output from a given set of inputs, and (ii) allocative efficiency, which reflects the ability of a firm to use the inputs in the optimal proportions, given their respective prices. These two components are then combined to provide a measure of total economic efficiency (overall efficiency). Farrell also introduced an input-oriented technical efficiency measure, defined as the ratio of minimum potential to the observed input required to produce the given output. Thus the analysis of technical efficiency can have an input-conserving orientation or an output-augmenting orientation. Efficiency is a relative measure; efficiency scores depend on the firms that are compared.

In the efficiency literature, methods to estimate the technical or economic performance are readily available. The two important methods to compute technical efficiency scores are (i) mathematical programming methods (e.g. Data Envelopment Analysis, DEA) and (ii) econometric methods (Stochastic Frontier Approach, SFA, cost functions and distance functions). According to Lovell (1993) there are two essential differences between the econometric approach and mathematical programming methods in the calculation of a frontier function. The econometric approach is stochastic, and so attempts to distinguish the effects of noise from the effects of inefficiency. DEA is non-stochastic, and lumps noise and inefficiency together, calling the combination inefficiency. The econometric approach is parametric, and confounds the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency. The mathematical programming approach is nonparametric and less prone to this type of specification error. DEA is extensively described by Charnes *et al*. (1995). Hjalmarsson *et al*. (1996) argue that one of the main appeals of the stochastic frontier approach is the possibility it offers for a specification in the case of panel data. It also allows for a formal statistical testing of hypotheses. Coelli (1995b) concluded that if one is using farm-level data where measurement errors, missing variables, the weather etc. are likely to play a significant role, then the assumption that all deviations from the frontier are due to inefficiency, (an assumption made by mathematical programming techniques) may be too bold. There is a long history of the econometric approach to efficiency measurement in agriculture (see Battese (1992) and Coelli (1995b) for an overview). In this dissertation, the primary focus is on econometric methods to compute environmental efficiency.

The Stochastic Frontier Approach (SFA) is motivated by the idea that deviations from the frontier might not be entirely under the control of the firm studied. The stochastic frontier approach was introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) and was later extended to panel data by Pitt and Lee (1982) and Battese and Coelli (1988, 1992). An alternative representation of production technology is the cost function. The cost function was adapted to estimate input-oriented technical efficiency and allocative efficiency (Schmidt and Lovell, 1979). This approach corresponds to Farrell's (1957) original efficiency measure. Kopp and Diewert (1982) approach the measurement of allocative inefficiency by analysing the cost-minimising demands implied by Shephard's lemma. Atkinson and Cornwell (1994a) adapted this approach into a shadow cost system and computed allocative inefficiency based on the difference between shadow prices and observed prices. In a shadow cost system deviations from optimal ratios of inputs are explicitly modelled by a price distortion factor (Kumbhakar, 1996; Atkinson and Cornwell, 1994a).

Although distance functions have been available since they were developed by Shephard (1953, 1970), it was only recently that applications involving distance functions appeared (Färe *et al*., 1993; Lovell *et al*., 1994; Grosskopf *et al*., 1997). The principal advantage of the distance function representation is that it allows for the possibility to specify a multiple-input, multiple-output technology when price information is not available or, alternatively, when price information is available but cost, profit or revenue representations are precluded because of violations of the required behavioural assumptions (Färe and Primont, 1995). Distance functions also provide performance measures, by providing a measure of the distance between each producer and the frontier technology. Econometric methods have been applied to estimate distance functions (Lovell *et al*., 1994; Coelli and Perelman, 1996; Grosskopf *et al*., 1997). In fact, the econometric estimation method for distance functions is still being developed (Atkinson *et al*., 1998; Atkinson and Primont, 1998; Vouldis *et al*., 2010). Overviews of econometric methods for efficiency estimates can be found in Greene (1997), Coelli *et al*. (1998) and Kumbhakar and Lovell (1999). When a two-stage approach is employed, the determinants of inefficiency are exogenous variables which are neither inputs to the production process nor outputs of it, but which nonetheless influence the process (Simar *et al*., 1994). In the literature various methods have been developed based on the error component that describes efficiency (e.g. Reifschneider and Stevenson, 1991; Huang and Liu, 1994; Battese and Coelli, 1995; Kumbhakar and Lovell, 1999).

The efficiency methodology has been applied to environmental problems. Färe *et al*. (1989) computed an environmental performance measure based on the firm's efficiency in the restricted situation (because of environmental legislation) and the unrestricted situation. Ball *et al*. (1994) and Tyteca (1997) define and compute various environmental performance measures for agriculture and the paper sector respectively. One of their measures compares observed emission to minimum emission of the bad output. The aforementioned studies all use mathematical programming methods. Hetemäki (1996) applied econometric efficiency methods to estimate technical efficiency based on bad outputs and conventional inputs and output. He computes shadow prices, but he neither defines nor estimates a measure of environmental efficiency.

The impact of pollution on the production process of the firm is modelled in several ways within the conventional neoclassical framework. Most models do not directly incorporate pollution into the models of production technology but enter the costs of abatement into a cost function (e.g. Conrad and Morisson, 1989; Barbera and McConnell, 1990) or a profit function (Boots *et al*., 1997). When the pollution is incorporated directly in the neoclassical framework the effluent is either specified in a production function (e.g. Pittman, 1981; Cropper and Oates, 1992) or in a profit function as an additional fixed input (Fontein *et al*., 1994). When pollution is incorporated in the neoclassical production model, the underlying assumptions have to be tested. Pittman (1981) found that the quasi-convexity required of the translog production function is not strictly satisfied.

1.5 Objectives of the study

This dissertation aims to define the production possibility frontier of the KwaZulu-Natal Midlands dairy industry as its main objective. The main objective will be achieved through addressing two other objectives, namely: 1) the estimation and calculation of technical efficiency of the dairy farms and 2) the estimation and calculation of the environmental efficiency of the farms in the Midlands of KwaZulu-Natal. Both technical efficiency and environmental efficiency will be estimated econometrically following the parametric stochastic frontier approach (SFA) and calculated following the nonparametric mathematical data envelopment analysis (DEA) approach.

Furthermore the objective of defining and measuring the technical efficiency of the dairy farms will be divided into sub-objectives for purposes of clarity. These are:

- Modelling the efficiency of the dairy farms
- Specifying alternative empirical stochastic approaches to production function estimation
- Using the mathematical programming data envelopment analysis (DEA) approach to efficiency computation
- Using the Malmquist total factor productivity (TFP) index approach for measuring productivity changes for the dairy farms

Similarly, the second objective of defining, estimation and evaluating environmental efficiency of the dairy farms in the KwaZulu-Natal Midlands will be sub-divided into two sub-problems, namely the econometric estimation of environmental efficiency by extending the stochastic frontier approach to incorporate an environmentally-detrimental variable ('bad') either as an input or output, and using the mathematical programming DEA approach to calculate environmental efficiency.

Environmental efficiency is a measure that allows for the combination of a firm's environmental pressure with its (economic) performance. Econometric models, based on the neoclassical production theory, are adapted to enable the definition and estimation of a farm's technical efficiency and environmental efficiency. The econometric (stochastic production frontier) and DEA methods are evaluated in this dissertation on their possibilities to compute environmental efficiency. These methods are applied to a panel of KwaZulu-Natal Midlands dairy farms. Pollution is incorporated in this framework in various ways. Nitrogen surplus is the environmentally detrimental variable throughout this dissertation, and it is computed with the materials balance condition. Finally, the variation in efficiency is explained based on characteristics that are hypodissertationed to influence environmental efficiency as in the two-stage modelling approach.

The following research questions pertaining to environmental efficiency are deduced:

1. How to define environmental efficiency? A definition of environmental efficiency is not yet agreed upon in the literature.
2. How to compute environmental efficiency econometrically?
3. How to model pollution in the neoclassical framework? A standard way to model pollution in the neoclassical framework is not available. The way to incorporate pollution appropriately into econometric efficiency models has to be determined.
4. How to deal with the materials balance condition? Nitrogen surplus is measured with a materials balance definition. This characteristic of the environmentally detrimental variable has not yet been incorporated in the efficiency framework.
5. How to explain environmental efficiency differences across farms? Various methods are available to explain efficiency differences. The method, that best suits the developed environmental efficiency scores, has to be selected and developed.
6. What is the best method to compute environmental efficiency scores?

In this dissertation the technical efficiency and environmental efficiency measures are estimated and computed econometrically and mathematically. These two broad categories of approaches need to be compared to select the best measure for analysing environmental performance.

1.6 The importance of the study and its contribution to knowledge

This study is divided into two main sub-problems, and subsequently two main research questions or hypotheses, with the first question focussing on technical efficiency, and the second on environmental efficiency, of dairy farms in the KwaZulu-Natal Midlands.

Generally, the study is important on two fronts. First, an understanding of the technical efficiency of the dairy farms in the Midlands of KwaZulu-Natal will help in understanding the sustainability and the financial position of most dairy farms in the KwaZulu-Natal Province. This will also help in understanding why dairy farms are becoming fewer and larger. It is a world-wide phenomenon that smaller dairy farms operate on the margins of profitability thus need to maintain the precarious balance between viability and profitability. It is worth finding out if small dairy farms in South Africa are less technically efficient than their large counterparts or whether farms are becoming larger simply to increase farm incomes to levels comparable with incomes derived from other sectors in the economy. The information on the technical efficiency of the farms will reveal if there are economies of scale in the dairy industry in the KwaZulu-Natal Midlands and if the farms are already larger than the optimal size, if there is an optimal size. Furthermore, the study will show if there has been technological improvement in the dairy sector through the measurement of the Malmquist total factor productivity index; this is important for policy making in that factors that contribute to productivity growth can be identified. The dissertation will also generate new information on how to best model the dairy industry which is a multi-input, multi-output production system: this has not been done before in the South African dairy industry. Another nuance to be gained from the dissertation is an evaluation of the best suitable model for estimating the production function of the dairy industry given the available data. Lastly, on the technical efficiency objective, the study will identify some factors that lead to inefficiency in the dairy industry and their importance, thus providing invaluable information to dairy farmers, extension services, other researchers and policy makers.

Next, the definition, estimation and evaluation of environmental efficiency of the dairy farms in the KwaZulu-Natal Midlands will be a major philosophical contribution in that no similar studies have been conducted in South Africa and there is a general paucity of reliable information elsewhere on the subject of environmental efficiency in the dairy industry. There is also no consensus in the literature on how to model environmental efficiency in agriculture. There are divergent views on whether the incorporation of pollution as an input or an output is the most desirable approach. In the dissertation attempts will be made to model environmental efficiency using both input- and output-oriented approaches and then to compare the results and which approach is most suited for modelling environmental efficiency in the dairy industry.

1.7 Data

The data used in this study were obtained from Alan Penderis of Tammac Consulting cc, a consultancy firm located in Ixopo (Southern KwaZulu-Natal) which assists dairy farmers in the Midlands with production and marketing services. The farms that were selected are highly specialised dairy producers deriving more than 90 percent of their income from dairying. The dataset covers 37 dairy farms, representing approximately 10 percent of the 381 dairy farms in the area in 2007. Thus, the group of farms used in this study could be considered as a sample of dairy farms in KwaZulu-Natal Midlands. The sample also comprised of farms of various sizes from all the different geographical areas of the KwaZulu-Natal Midlands thus representative of the parent population and inferences about the population are valid.

The dataset consists of dairy financial management data covering the nine years from 1999 to 2007. If it were a balanced panel it would comprise 333 observations, but there are only 25 farms for the first two years. Then the sample was increased to 37, but one farm dropped out in 2006 and only 22 farms had reported for 2007 at the point in time when the data were accessed. This gives an unbalanced panel with a total of 293 observations. The original data are all in terms of current prices, which does not allow for comparisons across time. The current price data is used first, to investigate the cross sections for the individual years, as using deflators is bound to introduce some amount of random error, but then the variables all need to be transformed to constant prices. The data and the various manipulations that will be done will be discussed in the data section in Chapter 4.

The variables used in the analysis of dairy production are a small subset of the data supplied. The production functions explain a single output with all the important inputs. The outputs thus have to be aggregated and so do the inputs, as there are far too many to include and they tend to be collinear. The farms sell milk (**product income in the accounts),** other milk products and some farm produced fodder (**other income**), but they also buy and sell animals (**trading income**), so these are the three components of the output variable. The variable **product income** is the net income for all milk sold, including cash sales (milk sold informally), after deducting transport charges, all levies and monthly shares deductions. Monthly shares are paid to marketing agents and professional service providers such as accountants and advisors and they are deducted each month. The price that farmers normally receive from processors depends on a number of milk characteristics, including butterfat and protein content and somatic cell count. Price differences between farmers are, therefore, the result of milk quality and component composition. Thus, using revenues for total output provides additional information. **Other income** includes bags sold; levies repaid; dividend and bonus received; surplus grain sales; grazing let; and land lease income. **Trading income**, by definition, is gross income (inclusive of levies, transport etc) for the sale of cull cows, breeding cows, heifers, bull calves and oxen. Cattle purchases and hire purchase (charges for purchase) redemption for cattle purchases are entered in parendissertation (as a negative value) next to the cattle sales figures. **Nitrogen surplus** is the environmentally detrimental variable which is the difference between the nitrogen input into the dairying system and the nitrogen utilized (contained) in marketable products. A positive difference represents excess nitrogen application leading to residuals which have the potential of being leaked into the environment thus causing pollution. The nitrogen surplus that will be used for the econometric estimation of environmental efficiency in Chapter 8 was calculated using nitrogen inputs and outputs in nitrogen-containing products and is calculated on a per hectare basis. The nitrogen surplus to be used in the mathematical programming DEA approach will be derived from a dataset of 34 farms for one year participating in a pasture-utilization improvement programme, after using the first nitrogen surplus from the econometric estimation in Chapter 8.

Specialised dairy farms were chosen for the estimation of environmental performance measures for data reasons, methodology reasons and policy relevance. There are a number of advantages for using such a dataset. One, dairy farms are well represented in the dataset since it provides a reasonable number of observations. Furthermore, specialised dairy farms have a similar production structure, and the results can be compared with the literature (e.g. Elhorst, 1990; Thijssen, 1992; Boots *et al*., 1997; Berentsen, 1999; Reinhard *et al*., 1999). Two, the number of different nutrient flows at farm level is larger for dairy farms than for other specialised farms, because dairy farming consists of two components: roughage production (pasturage) and livestock production (Dijk *et al*., 1996). If the environmental aspects of dairy farming can be modelled in this dissertation, then the method can also be used to describe the simpler production processes in the hog and poultry sectors.

1.8 Organisation of the dissertation

The dissertation is organised as follows: The current chapter, Chapter 1, gives a general background to the South African dairy industry and covers general technical efficiency and environmental efficiency concepts and the approaches to be used. Chapter 1 also discussed data that will be used and the contribution that work reported in the dissertation will make to the body of knowledge with justifications of undertaking the study.

Chapter 2 gives a review of production economics with regard to efficiency measures and the various theoretical approaches that have been used to study efficiency in economics, in general, and agriculture in particular. The review attempts to isolate those studies reported in the literature that are relevant to work done in the dissertation. A brief historical background to the development of efficiency studied is given, including developments in environmental efficiency, sometimes referred to as eco-efficiency in the literature. Lastly, Chapter 2 outlines the theoretical approaches that will be developed further in the dissertation.

Chapter 3 gives a background to dairy farming in South Africa and the KwaZulu-Natal Midlands. The KwaZulu-Natal Midlands is delineated as the study area thus it is discussed in detailed and its geographical location within South Africa is discussed along with its importance to dairy farming in the country. The latest trends in the dairy industry are discussed and their implications on efficiency are identified. Next the data that will be used for the study is discussed and preliminary analyses are done and reported on.

Chapter 4 deals with modelling of the efficiency of dairy farms using net and gross output and input approaches in order to better understand how to aggregate or disaggregate variables and then correctly measure efficiency.

Chapter 5 covers alternative empirical approaches to production function estimation. The dataset to be used is panel data. Panel data immediately confronts the researcher with choices which may be difficult. The correct level at which to estimate is seldom obvious. In this case, the first alternative, of estimating the time series separately, for each individual farm, is precluded by the lack of observations. With only nine data points, there are insufficient degrees of freedom to follow this option, although farms could be grouped according to size, to give several samples of sufficient size. This option becomes attractive if farm size is an issue and this will become apparent as results are generated.

The other disaggregated alternative, of estimating the cross sections for individual years is viable, although the samples are perhaps too small to expect good results. This approach, using the current price data, will be investigated first, before progressing to pooling the years or running the model as a panel. The different possible combinations of outputs and inputs (such as the three ways of calculating milk output) are all tried. The herd size will be included to test if cows should be used as an input. Then, experimentation shows that some variables have more explanatory power when they are lagged one year. The first issue to be tackled is then choice of the functional form for the production function, which is done by testing the adequacy of the restrictive Cobb-Douglas against a flexible functional form. Then, for the panels, the preferred model has to be tested against for consistency against the more restrictive fixed effects model.

Chapter 6 looks at DEA approach to efficiency calculation. Intuitively, given that there are two broad approaches to efficiency studies, namely parametric and non-parametric, it becomes useful to look at both in a study of the nature of this work. Consequently, the current chapter will employ the DEA approach which is both non-parametric and deterministic. However, the DEA has some advantages or features that the stochastic frontier approach does not possess thus it is attractive go into the DEA approach to glean some in-depth information and could have been lost or not identified in the previous chapter.

The DEA is a mathematical programming approach for measuring technical efficiency and economic performance of firms. Charnes *et al*. (1978) are accredited for formally introducing DEA, albeit their work being actually an extension of the works of Shephard (1953, 1970) and Farrell (1957). DEA facilitates the construction of a non-parametric piece-wise frontier over the existing data. Efficiency measures are then derived by exploring the distances between observed input and output combinations and frontier input and output combinations (sometimes referred to as ratios).

Chapters 7 gives results of the Malmquist Total Factor Productivity (TFP) index to measuring productivity changes in KwaZulu-Natal dairy industry over the years. The Malmquist Total Factor Productivity (TFP) index methodology was selected because it does not need prices to get weights and the data used do not have prices for individual inputs.

Chapters 8 and 9 develop methodological approaches for measuring environmental efficiency for the dairy farms in KwaZulu-Natal Midlands. Chapter 8 reports results of the estimation of technical and environmental efficiency of a panel of dairy farms in the KwaZulu-Natal Midlands. It is necessary to also estimate technical efficiency, although this is not the main thrust of the work reported in this chapter, because this facilitates better contextualization of environmental efficiency. The inclusion of technical efficiency when dealing with environmental efficiency also helps in making comparison between the two types of efficiency possible. In this chapter the nitrogen surplus will be treated as an environmentally detrimental input. Nitrogen surplus emanates from the application of chemical nitrogenous fertilizer (main source), animal excretion in the form of manure (dung) and urine, and biological and atmospheric fixation in excess to quantities required by plants (for pasture and silage) for their growth and in excess of the soil's nitrogen mineralization capacity (Mkhabela, 2002; Reinhard *et al*., 1999). Manure can be viewed both as an asset (free organic fertilizer for plant growth) and liability where it is produced in excess of the farm's manure carrying capacity and its disposal costly (Mkhabela, 2002). Excess nitrogen can escape to the environment (soil, air and water) where it can cause environmental problems through pollution. These environmental problems include: 1) the eutrophication of surface water thus endangering plant and fish life and reducing aesthetic value of surface water such as lakes and dams; 2) leaching of nitrates into groundwater aquifers; 3) evaporation of ammonia (gaseous form of nitrogen) into the atmosphere, technical known as volatilization, which contributes to acid rain (Reinhard *et al.*, 1999).

Chapter 9 reports results of the nonparametric calculation of environmental efficiency the KwaZulu-Natal Midlands dairy farms. The results reported here in Chapter 9 are for environmental efficiency of the dairy farms and it will be measured in terms of efficiencies in the utilization of nitrogen as indicated by surplus nitrogen production. Nitrogen surplus is the difference between the applied nitrogen plus the nitrogen contained in marketable products and the nitrogen that remains on the farm (excess nitrogen that was not used in the production of the desirable outputs – milk, pasture and meat products). Lastly, Chapter 10 draws conclusions from the results and makes some policy recommendations.

Chapter 2: A review of theoretical approaches

2.1 The production function and its parameters

There are three basic methods that are conventionally used to measure and explain efficiency and productivity in the literature. There is the econometric estimation of the production function; the accounting approach using index number theory to measure total factor productivity (TFP) (Thirtle, 2000:73); and non-parametric programming techniques, commonly known as data envelopment analysis (DEA). The data envelopment analysis leads to a TFP index known as the Malmquist index which is different from the accounting approach index. In the empirical chapters (Chapters 5, 6, 7 and 8) these approaches are applied to the dairy industry in the Midlands of KwaZulu-Natal. These approaches may be different, but they are complimentary as will become apparent. Thirtle (2000) stated that these methods focus on different aspects of the production function and thus generate different information.

The basic definition of a production function is the maximum output that can be produced with a given input combination for a particular technology[2], thus technology is the basic element of a production function. The detail and accuracy of a production function depends on its use. In this chapter it is presented in more generic terms in a general theoretical context than in specific empirical applications. The basic assumptions of production functions can be graphically illustrated using two graphs. The first graph (Figure 1) represents output as a function of input and introduces the three stages of production; Let y = output and x = input. The production function is y = f(x); marginal productivity (MP) is $f_x = \partial f/\partial x$; and average product (AP) is y/x. Notice the following as depicted in Figure 1:

$MP > AP > 0$ at Stage I of the production function

$AP > MP \geq 0$ at Stage II of the production function

$MP < 0$ at Stage III of the production function

[2] Kumbhakar and Lovell (2000:25-26) define a production function or frontier as a representation of maximum output that can be obtained from any given input vector or, alternatively, the minimum input usage required to produce any given output vector.

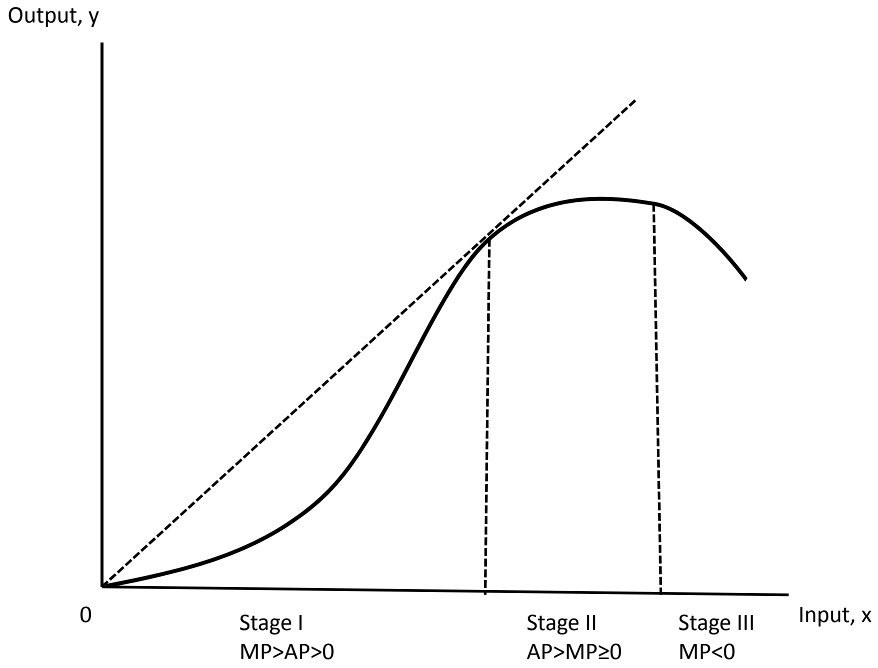

Figure 1: Three stages of production

The Cobb-Douglas can be outside the productive region – any negative elasticity means that the MP is negative and greater than unity is also possible. These results are usually deemed to be unacceptable because they do not correspond to the productive region. However, that in dairying in South African this would not be too unreasonable as there are number of farmers making a loss for some years.

The second stage, stage II on Figure 1, shows the economic region of production. The economic region represent the stage with positive but decreasing marginal productivity, often referred to as the concave production function. This is the stage of the production function where a competitive profit-maximizing firm is likely to be found operating. Stage III is considered inefficient because the addition of an extra unit of, say labour (x_2) results in a decline in output and for Stage I, the addition of an extra unit of labour results in an increase in the average product of all labour units employed (Coelli *et al*., 1998:14). The relationships between inputs in the production process are shown in the isoquant diagram of Figure 2. The isoquants represent the different efficient input combinations producing the same level of output. The greatest value of the isoquants depicted is their usefulness in understanding factor ratios and input substitutability for a given production process. If x_1 is capital and x_2 is labour (Figure 2), then $\frac{x_1}{x_2}$ measures capital intensity relative to labour. Production at point A is relatively capital intensive and at point B production is relatively labour intensive.

The ability to assess the ease of replacing one input for another while keeping output fixed is of interest to economists and policy-makers, alike. The first extreme case is no substitutability. For a production function with fixed proportions (Leontief type):

$$y = \min\left\{\frac{x_1}{\alpha_1}, \frac{x_2}{\alpha_2}\right\} \quad \textbf{(2.1)}$$

the isoquant for each production level is L shaped, allowing the substitutability

$$\left(x_1 = \frac{y}{\alpha_1}, x_2 = \frac{y}{\alpha_2}\right) \quad \textbf{(2.2)}$$

and input intensity is constant at $x_1/x_2 = \alpha_1/\alpha_2$. For a linear production function, $y = \alpha_1 x_1 + \alpha_2 x_2$, the isoquant is a straight line, $x_1 = y/\alpha_1 - \alpha_2 x_2/\alpha_1$, and there are infinite substitution possibilities.

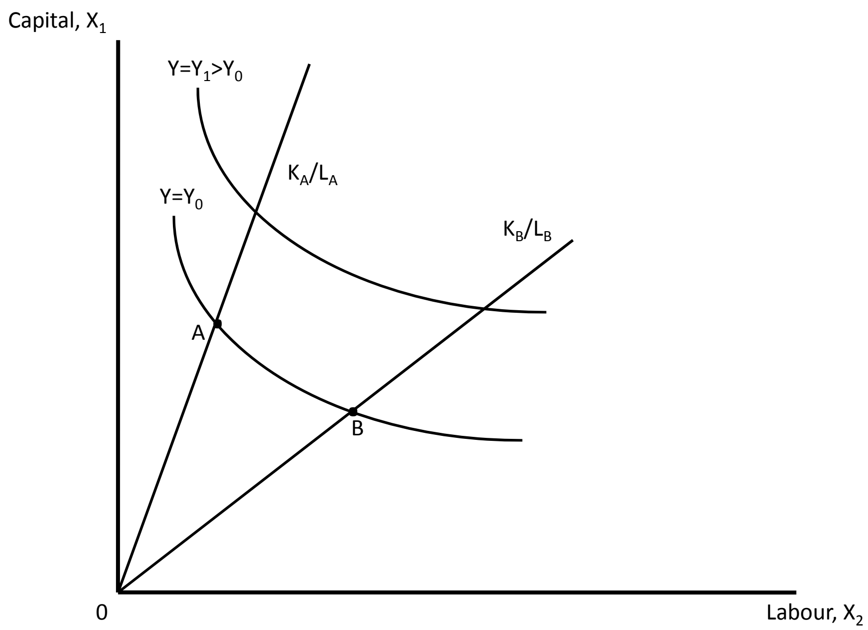

Figure 2: Isoquants and factor intensity

Figure 2 shows a less extreme case, where there is some substitutability, but it is less than infinite. For example, the Cobb-Douglas: $y = Ax_i^{\alpha_i}$ has unitary elasticity of substitution between all input pairs. Let the parameters be: the input elasticity, α_i; the scale elasticity, ε; and the elasticity of substitution, σ_{ij}. For the general case let $y = f(x_1, x_2, ..., x_n)$ be a production function; y = output; and x_i = inputs, then the following quantities can be defined:

$$f_i = \frac{\partial f}{\partial x_i} = \text{ marginal product of input i} \quad \textbf{(2.3)}$$

$$\alpha_i = \frac{\partial f}{\partial x_i}\frac{x_i}{y} = f_i \frac{x_i}{y} = \text{ output elasticity of input i} \quad \textbf{(2.4)}$$

$$\varepsilon = \sum_{i=1}^{n} \alpha_i = \text{ scale elasticity} \quad \textbf{(2.5)}$$

Note that the elasticity of substitution between input *i* and *j* is denoted as σ_{ij}. Taking a case of two inputs, x_1 and x_2, the elasticity of substitution between x_1 and x_2 is:

$$\sigma_{12} = -\frac{\partial(x_1/x_2)}{\partial(f_1/f_2)} \Big/ \frac{(x_1/x_2)}{(f_1/f_2)} = -\frac{d\ln(x_1/x_2)}{d\ln(f_1/f_2)} \quad \textbf{(2.6)}$$

This elasticity of substitution is a measure of the ease of change in input intensity. An elasticity of substitution of zero ($\sigma = 0$) implies a fixed proportion production function and input intensity does not change. The extreme opposite of a fixed proportions production function is the linear production function ($y = ax_1 + a_2x_2$), in which case $\sigma = \infty$ and input intensity can be easily changed. Figure 2 shows an intermediate case, such as the Cobb-Douglas, in which $\sigma = 1$. In all these cases the elasticity of substitution is imposed by the functional form rather than being estimated, so they are highly restrictive. Concisely put, returns to scale (RTS) is a long run concept which reflects the degree to which a proportional increase in all inputs increases output (Coelli *et al*., 1998).

2.2 Econometric estimation

An important starting point is recognizing that all the approaches and subsequent representations have, as their genesis, the basic concept of a relationship between outputs, Y_i and inputs, X_j. The easiest way to discuss this relationship is to take the simplest general form with the single output production function, $Y = F(X_j)$ as the starting point. It has to be realized that this single output production function is strictly a technical relationship. However, economics can easily be introduced by stating an economic problem such as profit maximization with the production function as the technological constraint (Thirtle, 2000; Thirtle *et al*., 2000). There have been considerable theoretical advances that have been applied to both the econometric approach and in the accounting techniques, the most salient of which have been the development of flexible functional forms and duality theory. These are discussed in the following section, albeit briefly, because these and other theoretical approaches are discussed in more details when they are applied in the results chapters. Then a discussion of the programming techniques (DEA), which are used to calculate the Malmquist TFP index, follows.

2.3 Flexible functional forms

The original Cobb-Douglas production function is linear in logarithms and the coefficients in equation are output elasticities:

$$LnY = Ln\alpha_0 + \alpha_1 LnX_1 + \alpha_2 LnX_2 + ... + \alpha_n LnX_n \quad \textbf{(2.7)}$$

Because the Cobb-Douglas function is unduly restrictive, flexible functional forms such as the translog were developed to circumvent this restrictiveness. The main area of difference between these flexible functional forms and the Cobb-Douglas is that the former incorporate enough estimated parameters to capture the interactions between variables and to allow for non-linearity in the parameters. The translog is commonly specified as:

$$LnY = Ln\alpha_0 + \sum_i \alpha_i LnX_i + \frac{1}{2}\sum_i \sum_i \beta_{ij} LnX_i LnX_j \quad \textbf{(2.8)}$$

Where Y is aggregate output, the X_is are inputs and all the α_is and the β_{ij}s are the coefficients. Looking at Equation (2.8), it is clear that without the last term it is a Cobb-Douglas production function. The last term is what allows for interactions between inputs, when $i \neq j$. These terms allow the elasticities of substitution between each pair of inputs to be estimated from the data. The Cobb-Douglas, however, imposes substitution elasticities of unity for all pairs of inputs.[3] So, under the translog, if two inputs are compliments rather than substitutes such as expenditure on veterinary services and artificial insemination for the dairy industry, this would be taken into account. The last term, $i = j$, can add squared terms for each input thus allowing for non-linearity and leading to the quadratic which is another example of a flexible form (Coelli *et al.*, 1998:35). Flexible functional forms provide a second-order local approximation to any underlying true functional form.

Only those functional forms that will be used later on in this dissertation are mentioned in this section. However, for more comprehensive information on the properties of various functional forms see Beattie and Taylor (1985).

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[3] The output elasticities in the Cobb-Douglas are also the factor shares, under constant returns to scale, and are constant. This imposed unity can only be true if changes in prices are met with commensurate changes in quantities because this requires unitary elasticities of substitution for all pairs of variables.

2.4 The measurement of technical change

It is possible to estimate the rate of technological change in an industry if time-series, cross-section and/or panel data are available by including a time-trend variable in an econometric production function. Time series data refers to data collected on an individual firm over time; cross-section data refers to data collected for more than one firm for a particular time period; while panel data refers to the combination of both time-series and cross-section data, that is, data collected from more than one firm over more than one time period. Taking the Cobb-Douglas production function as an example, Equation 2.7 can be specified as:

$$LnY = Ln\alpha_0 + \alpha_1 LnX_1 + \alpha_2 LnX_2 + \alpha_t t \qquad \textbf{(2.9)}$$

Where t is a time trend (t=1,2,…,T). The estimate of the coefficient, α_t, provides an estimate of the annual percentage change in output resulting from technological change (Coelli *et al.*, 1998).

Similarly, the translog production function given in Equation 2.8 can be adjusted to account for technological change. Given that the translog is a second-order approximation, as already discussed; both t and t^2 are often introduced to the equation to yield:

$$LnY = Ln\alpha_0 + \sum_i \alpha_i LnX_i + \frac{1}{2}\sum_i \sum_i \beta_{ij} LnX_i LnX_j + \alpha_t t + \alpha_{tt} t^2 \qquad \textbf{(2.10)}$$

In Equation 2.10, an estimate of the annual percentage change in output due to technological change is given by the first partial derivative of the equation in regard to t: $\alpha_t + 2t\alpha_{ii}$. Ordinarily, the value of technological change will vary with varying values of t. It will decrease over the sample period if α_{ii} is negative and increase if α_{ii} is positive.

2.5 Measures of economic efficiency

Economic efficiency can be divided into two distinct components, namely, technical and allocative efficiency. The technical part is a measure of the ability to avoid waste, either by producing as much output as technology and input usage allow (output-maximization) or by using as little input as required by technology and output production (input-minimization). It, therefore, follows that the analysis of technical efficiency can have an output augmenting orientation or an input conserving orientation. The allocative component refers to the ability to combine inputs and/or outputs in optimal proportions given the prevailing prices. Optimal proportions satisfy the first-order conditions for the optimization problem assigned to the production unit.

Koopmans (1951) formally defined technical efficiency by stating that a producer is technically inefficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Thus a technically efficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output.

However, it was Debreu (1951) and Farrell (1957) who introduced a measure of technical efficiency. With an input conserving (minimizing) orientation their measure is defined as the maximum equi-proportionate (often referred to as radial) reduction in all inputs that is feasible with given technology and outputs. The measure of technical efficiency devised by Debreu (1951) and Farrell (1957) will be referred to as the Debreu-Farrell measure in this chapter for brevity. With an output augmenting (maximization) orientation their measure is defined as the maximum radial expansion in all outputs that is feasible with given technology and inputs. In both orientations a value of unity indicates technical efficiency because no radial adjustment is feasible, and a value different from unity indicates the severity of technical inefficiency.

In order to relate the Debreu-Farrell measures to the Koopmans definition, and to relate both to the structure of production technology, it is useful to introduce some notation and terminology. Let producers use inputs $x = (x_1,\ldots,x_N) \in R^N_+$ to produce outputs $y = (y_1,\ldots,y_M) \in R^M_+$. Production technology can be represented by the production set

$$T = \{y, x\}: x \text{ can produce } y. \qquad \textbf{(2.11)}$$

Based on Equation 2.11, Koopmans' definition of technical efficiency can now be stated formally as $(y,x) \in T$ is technically efficient if, and only if, $(y',x') \notin T$ for $(y',-x') \geq (y,-x)$.
Technology can also be represented by input sets

$$L(y) = \{x : (y, x) \in T\}, \qquad \textbf{(2.12)}$$

and these input sets have input isoquants for every $y \in R^M_+$

$$l(y) = \{x : x \in L(y), \lambda x \notin L(y), \lambda < 1\} \quad \textbf{(2.13)}$$

and input efficient subsets

$$E(y) = \{x : x \in L(y), x' \notin L(y), x' \le x\} \quad \textbf{(2.14)}$$

and the three sets satisfy $E(y) \subseteq l(y) \subseteq L(y)$

Shephard (1953) introduced the input distance function to provide a functional representation of production technology. The input distance function is

$$D_I(y,x) = \max\{\lambda : (x/\lambda) \in L(y)\}. \quad \textbf{(2.15)}$$

For $x \in L(y), D_I(y,x) \ge 1$,and for $x \in I(y), D_I(y,x) = 1$. Given standard assumptions on T, the input distance function $D_I(y,x)$ is non-increasing in y, and non-decreasing, homogeneous of degree +1 and concave in x.

The Debreu-Farrell input-oriented measure of technical efficiency can now be given a somewhat more formal interpretation as the value of the function

$$TE_I(y,x) = 1/D_I(y,x) \quad \textbf{(2.16)}$$

and it follows from (2.15) that

$$TE_I(y,x) = 1/D_I(y,x). \quad \textbf{(2.17)}$$

for $x \in L(y), TE_I(y,x) \ge 1$, and for $x \in I(y), TE_I(y,x) = 1$.

Given that the bulk of efficiency measurement leans heavily toward output augmentation, it would be handy to replicate the above development in that direction. Production technology can be represented by output sets:

$$P(x) = \{y : (x, y) \in\}. \tag{2.18}$$

which for every $x \in R^N_+$ have output isoquants

$$l(x) = \{y : y \in P(x), \lambda y \notin P(x), \lambda > 1\} \tag{2.19}$$

and output efficient subsets

$$E(x) = \{y : y \in P(x), y' \notin P(x), y' \geq y\}, \tag{2.20}$$

and the three sets satisfy $E(x) \subseteq l(x) \subseteq P(x)$.

Another functional representation of production technology is provided by the Shephard (1970) output distance function:

$$D_0(x, y) = \min\{\lambda : (y / \lambda) \in P(x)\}. \tag{2.21}$$

For $y \in P(x)$, $D_o(x,y) \leqq 1$, and for $y \in I(x)$, $D_o(x,y) = 1$. Given standard assumptions on T, the output distance function $D_o(x,y)$ is non-increasing in x, and non-decreasing, homogeneous of degree +1 and convex in y.

A more formal interpretation of the Debreu-Farrell output-oriented measure of technical efficiency can now be given as the value of the function:

$$TE_0(x, y) = \max\{\varphi : \varphi y \in P(x)\}, \tag{2.22}$$

and it follows from Equation (2.21) that

$$TE_0(x, y) = [D_0(x, y)]^{-1}. \tag{2.23}$$

for $y \in P(x)$, $TE_0(y, x) \geq 1$, and for $y \in l(x)$, $TE_0(x, y) = 1$. A word of caution here is in order as some authors replace Equations (2.22) and (2.23) with $TE_0(x, y) = [\max\{\varphi : \varphi y \in P(x)\}]^{-1} = D_0(x, y)$, so that $TE_0(x, y) \le 1$ just as $TE_I(y, x) \le 1$. In this dissertation, the convention followed is of defining efficiency of any sort as the ratio of optimal to actual output. As a result $TE_I(y, x) \le 1$ and $TE_0(y, x) \ge 1$. The analysis presented so far assumes that M>1, N>1. In the single input case:

$$D_I(y, x) = x/g(y) \ge 1 \Leftrightarrow x \ge g(y), \qquad \textbf{(2.24)}$$

where g(y) = min{x: x $\in$ L(y)} is an input requirement frontier that defines the minimum amount of scalar input x required to produce output vector y. In this case the input-oriented measure of technical efficiency (3.17) becomes the ratio of minimum to actual input

$$TE_I(y, x) = 1/D_I(y, x) = g(y)/x \le 1. \qquad \textbf{(2.25)}$$

In the single output case:

$$D_0(x, y) = y/f(x) \le 1 \Leftrightarrow y \le f(x), \qquad \textbf{(2.26)}$$

where f(x) = max{y: y $\in$ P(x)} is a production frontier that defines the maximum amount of scalar output that can be produced with input vector x. In this case the output-oriented measure of technical efficiency in (3.23) becomes the ratio of maximum to actual output

$$TE_0(x, y) = [D_0(x, y)]^{-1} = f(x)/y \ge 1 \qquad \textbf{(2.27)}$$

The two technical efficiency measures are illustrated in Figures 3, 4 and 5. As a preview to the more substantial discussions that will be rendered in the result Chapters (5 to 8), technology is smooth in Figure 3 and piecewise linear in Figures 4 and 5. This reflects different approaches to using data to estimate technology. The econometric approach introduced in Section 2.2 and developed further in Chapters 4 and 5 estimates smooth parametric frontiers, while the mathematical programming approach introduced in Section 2.4 and further developed in Chapters 6 and 7 estimates piecewise linear nonparametric frontiers.

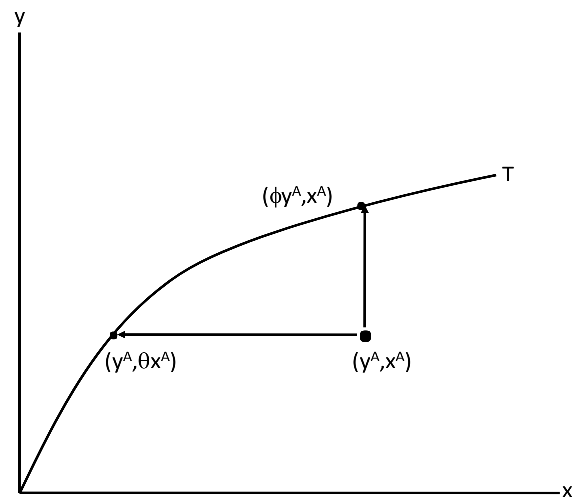


Figure 3: Basic technical efficiency

In Figure 3 producer A is located on the interior of T, and its efficiency can be measured horizontally with an input conserving orientation using (2.16) or vertically with an output augmenting orientation using (2.22). If an input orientation is selected, $TE_I(y^A, x^A) = \theta x^A / x^A \le 1$, while if an output orientation is selected, $TE_0(x^A, y^A) = \varphi\, y^A / y^A \ge 1$.

It is also possible to combine the two directions by simultaneously expanding outputs and contracting inputs, either hyperbolically or along a right angle, to arrive at an efficient point on the surface of T between $(y^A, \theta x^A)$ and $(\varphi y^A, x^A)$. A hyperbolic measure of technical efficiency is defined as:

$$TE_H(y,x) = \max\{\alpha : (\alpha y, x/\alpha) \in T\} \ge 1, \qquad \textbf{(2.28)}$$

and $TE_H(y,x)$ is the reciprocal of a hyperbolic distance function $D_H(y,x)$. Under constant returns to scale, $TE_H(y,x) = [TE_0(x,y)]^2 = [TE_I(y,x)]^{-2}$, and $TE_H(y,x)$ is dual to a profit function. One version of a directional measure of technical efficiency is defined as:

$$TE_D(y,x) = \max\{\beta : [(1+\beta)y, (1-\beta)x] \in T\} \ge 0, \qquad \textbf{(2.29)}$$

and $TE_D(y,x)$ is equal to a directional distance function $D_D(y,x)$. Even without constant returns to scale, $TE_D(y,x)$ can be related to $TE_0(y,x)$ and $TE_I(y,x)$, and is dual to a profit function. The directional measure and its underlying directional distance function are employed to good advantage in Chapter 5 dealing with stochastic frontier analysis and subsequent results for the dairy industry in the KwaZulu-Natal Midlands.

In Figure 4 input vectors x^A and x^B are on the interior of L(y) thus both can be contracted radially and still retaining the capability of producing output vector y. Input vectors x^C and x^D cannot be contracted radially and still remain capable of producing output vector y because they are located on the input isoquant I(y). Consequently, $TE_I(y,x^C) = TE_I(y,x^D) = 1 > \max\{TE_I(y,x^A), TE_I(y,x^B)\}$. Since the radially scaled input vector $\theta^B x^B$ contains slack in input x_2, there may be some hesitancy in describing input vector $\theta^B x^B$ as being technically efficient in the production of output vector y. No such problem occurs with radially scaled input vector $\theta^A x^A$. Thus $TE_I(y,\theta^A x^A) = TE_I(y,\theta^B x^B) = 1$ even though $\theta^A x^A \in E(y)$ but $\theta^B x^B \notin E(y)$. In summary, input orientation means minimising inputs for a given level of output and output orientation refers to maximising output for given input levels. However input and output orientations are the same under constant returns to scale.

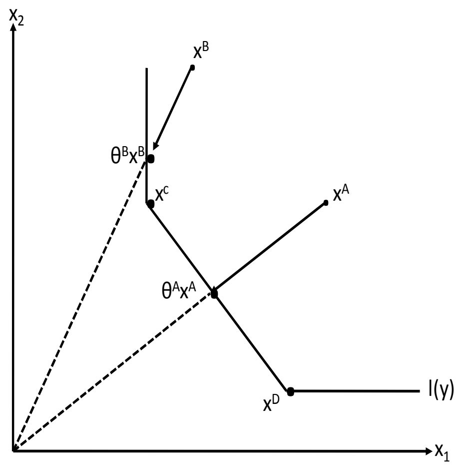


Figure 4: Input-orientation technical efficiency

The scenario depicted in Figure 5 is quite similar to the information contained in Figure 4, except that Figure 5 depicts the transformation function instead of the isoquants. Output vectors y^C and y^D

are technically efficient given input usage x, and output vectors y^A and y^B are not. Radially scaled output vectors $\phi^A y^A$ and $\phi^B y^B$ are technically efficient, even though slack in output y_2 remains at $\phi^B y^B$. Thus $TE_0(x, \phi^A y^A) = TE_0(x, \phi^B y^B) = 1$ even though $\phi^A y^A \in E(x)$ but $\phi^B y^B \notin E(x)$.

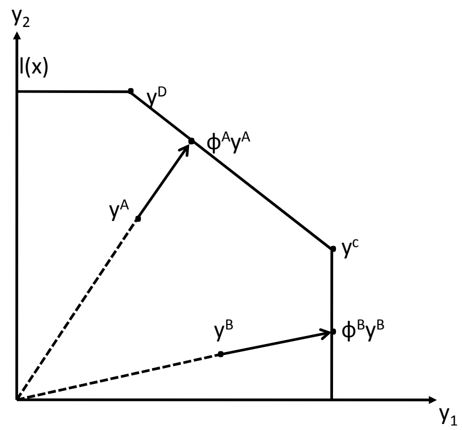


Figure 5: Output-oriented technical efficiency

The Debreu-Farrell measures of technical efficiency are used extensively for analyzing efficiency of production, since they satisfy a number of desirable properties (Shephard, 1970) and later by Russell (1988 and 1990) given that they are reciprocals of distance functions. These desirable properties are, *inter alia*:

- $TE_I(y,x)$ is homogeneous of degree -1 in inputs, and $TE_o(x,y)$ is homogeneous of degree -1 in outputs;
- $TE_I(y,x)$ is weakly monotonically decreasing in inputs, and $TE_o(x,y)$ is weakly monotonically decreasing in outputs; and
- $TE_I(y,x)$ and $TE_o(x,y)$ are invariant with respect to changes in units of measurement

Despite the desirable properties listed, the Debreu-Farrell measures are not perfect. A conspicuous drawback of the Debreu-Farrell measures of technical efficiency is that they do not satisfy the more rigorous demands of the Koopmans definition of technical efficiency. Koopmans' definition requires the absence of coordinate-wise improvements (that is, concurrent membership in both efficient subsets). The Debreu-Farrell measures, however, require only the absence of radial improvements (that is, membership in isoquants). So the Debreu-Farrell measures identify all Koopmans-efficient producers as being technically efficient, but also include any other producers located on an isoquant outside the efficient subset in the efficient list. Consequently Debreu-Farrell technical efficiency is necessary but not sufficient, when measured against the Koopmans technical efficiency. The possibilities are illustrated in Figures 4 and 5, where $\theta^B x^B$ and $\phi^B y^B$ satisfy the Debreu-Farrell conditions but not the Koopmans requirement because slacks remain at the optimal radial projections.

It should be stated that the practical significance of the Debreu-Farrell drawback discussed depends on the number of observations that lie outside the frontier of the relevant efficient subset. It is then not surprising that the problem becomes inconsequential in many econometric analyses using a functional form which imposes equality between isoquants and efficient subsets, thereby eliminating slack by assuming it away in estimating the production function (for example, Cobb-Douglas, but not flexible functional forms such as the translog). The disadvantage, however, is more important and serious in the mathematical programming approach, in which the nonparametric form of the frontier used to estimate the boundary of the production set imposes slack by a strong or free disposability assumption.

There are three main strategies that have been proposed in the literature to circumvent this problem. Firstly, Färe and Lovell (1978) suggested replacing the radial Debreu-Farrell measure with a non-radial measure that projects efficient subsets. This strategy ensures that an observation or its projection is technically efficient only if it is efficient in Koopmans' sense. However, this property is achieved at the expense of sacrificing the homogeneity property. Secondly, Cooper *et al*. (1999) suggested developing a measure that incorporates slack and the radial component into an inclusive measure of technical efficiency. Thirdly, the Debreu-Farrell shortcoming can be 'corrected for' by eliminating slack altogether by enforcing strictly positive marginal rates of substitution and transformation.

2.4 The Data Envelopment Analysis (DEA) approach

Prior to any detailed description of the DEA method, both input-oriented and output-oriented efficiency measures are discussed, as these will be used in Chapters 6, 7 and 8 later on. Farrell (1957) used a two-input and single-output constant returns-to-scale example to demonstrate his ideas.

In Figure 6, two inputs, X_1 and X_2, are represented on the horizontal and vertical axes, respectively. $SS^/$ is an isoquant representing various combinations of inputs (X_1 and X_2) used to produce a certain quantity of output (Y). All points on this isoquant reflect technically efficient production. An effort is made to measure the efficiency of a particular firm, which is operating at a point P. At this point (P), the particular firm produces the same level of output (Y) as produced on isoquant, $SS^/$. To define the technical efficiency of the observed firm, a line is drawn from the origin to the point P. This line crosses the isoquant at the point Q. In the case of a technically efficient firm, the same amount of output (Y) is produced using inputs (X_1 and X_2) defined by the point Q. Inputs are not used efficiently by observed firm P. So the technical efficiency (TE) of the observed firm is defined as the ratio of the distance from the point Q to the origin, over the distance of the point P from the origin:

$$\mathrm{TE} = \mathrm{OQ}/\mathrm{OP}. \qquad \textbf{(2.30)}$$

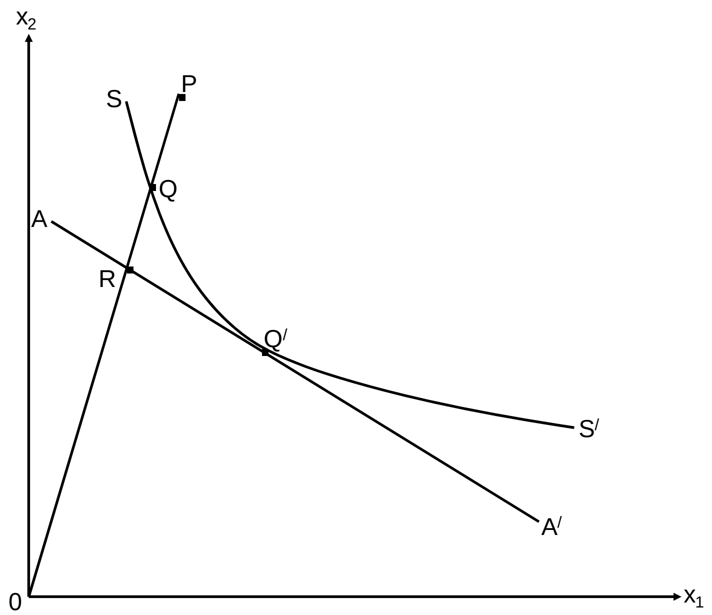


Figure 6: Technical and allocative efficiencies in input-oriented measures

In most production datasets in agriculture information on input prices is often lacking. However, if the input prices are available, allocative efficiency could also be defined. An iso-cost line, $AA^/$, is drawn tangential to the isoquant, $SS^/$, at the point $Q^/$, which intersects the line OP at the point R. For the output quantity produced at the point Q, the best use of inputs is at the point $Q^/$ because it incurs the minimum cost. Therefore, the point Q is not an optimal point because the distance, RQ (cost), can be reduced without any reduction in output. Allocative efficiency (AE) is defined as the ratio of the distance of the point R to the origin over the distance of the point Q from the origin:

$$AE = OR/OQ\,. \tag{2.31}$$

Economic efficiency (EE) is the product of technical efficiency and allocative efficiency:

$$EE = (OQ/OP)(OR/OQ) = OR/OP\ . \tag{2.32}$$

Technical, allocative and economic efficiencies are calculated using DEA methods. Technical efficiency is calculated using the input-oriented variable returns to scale (VRS) DEA model. The VRS model is discussed below. This is followed by a discussion of the DEA-Cost model. The exposition, which follows, is based upon Coelli *et al*. (1998).

2.4.1 Technical efficiency

Suppose data are available on K inputs and M outputs in each of N firms. Input and output vectors are represented by the vectors, x_{it} and y_{it}, respectively, for the i-th firm in t-th time period. The data for all firms may be denoted by the K×NT input matrix (X) and the M×NT output matrix (Y). The envelopment form of the input-oriented VRS DEA model is specified as follows:

$$\begin{aligned}
&\min \theta, \lambda\theta, \\
&st - y_{it} + Y\lambda \geq 0 \\
&\theta x_{it} - X\lambda \geq 0, \\
&N1/x\lambda = 1 \\
&\lambda \geq 0,
\end{aligned} \tag{2.33}$$

where θ is the input technical efficiency measure (scalar) having a value 0≤0≤1. If the θ score is equal to one, it indicates that the firm is on the frontier (Farrell, 1957). The vector λ is an NT×1 vector of weights which defines the linear combination of the peers of the i^{th} firm in the t^{th} period. The linear programming problem needs to be solved NT times, providing a value of θ for each firm in the sample.

2.4.2 Economic efficiency

The cost-minimizing vector of input quantities for the i^{th} firm in the t^{th} time period is calculated using the cost minimization DEA model. The model is specified below.

$$\begin{aligned}
&\min\lambda, x_{it} \\
&Ex_{it} \\
&EW_{it} \\
&st - y_{it} + Y\lambda \geq 0, \\
&x_{it} \\
&E - X\lambda \geq 0, \\
&N1/\lambda = 1 \\
&\lambda \geq 0
\end{aligned} \qquad \textbf{(2.34)}$$

where w_{it} is a vector of input prices for the i[th] firm in the t[th] time period and $x_{it;}$ E is the cost-minimizing vector of input quantities for the i[th] firm in the t[th] time period. Economic efficiency is calculated by dividing minimum cost by observed cost. Economic efficiency = minimum cost/observed cost, or

$$\begin{aligned}
&EE = w_{it} \\
&Ex_{it} / x_{it} w_{it}
\end{aligned} \qquad \textbf{(2.35)}$$

2.4.3 Allocative efficiency

Allocative efficiency is only discussed for background and informational purposes as this will not be used for analysis in this dissertation because there were insufficient input price data. Allocative efficiency is calculated by dividing economic efficiency by technical efficiency. Allocative efficiency = economic efficiency/technical efficiency or

$$AE = EE/TE, \qquad \textbf{(2.36)}$$

where TE is obtained from equation (2.33). Efficiency scores are obtained using the computer program, DEAP Version 2.1, described in Coelli (1996).

2.5 Theoretical development of environmental efficiency measurement

The notion of environmental efficiency and its measurement are relatively recent. However, a number of different approaches have been proposed and some used empirically in the past and these can be categorized into two broad groups, namely those which adjust conventional indexes of productivity change and those which adjust conventional measures of technical efficiency (Graham, 2004). According to Tyteca (1996) who reported on the general research methods, the approaches used have been, by and large, to consider environmental effects as undesirable outputs and to recalculate the technical inefficiency accounting for these undesirable environmental effects (Tyteca, 1996). Technical efficiency is measured while accounting for pollution, essentially in the form of undesirable outputs. The methods used to quantify efficiency vary with regard to the assumptions on the outer bound of the frontier, which may be either deterministic or stochastic, and with regard to the measurement approach, which may either be non-parametric or parametric.

Pitman (1983) was among the first to incorporate environmental effects into production efficiency estimates. Both desirable and undesirable outputs were taken into consideration in developing a multilateral productivity measure, in which environmental effects were treated as additional undesirable outputs whose disposal is costly. This approach raises the need for shadow prices since undesirable outputs are not generally priced in markets.

Fare *et al*. (1989) also treated environmental effects as undesirable outputs and developed an enhanced hyperbolic productive efficiency measure that evaluates a producer's performance in terms of the ability to obtain an increase in desirable outputs and a reduction in undesirable outputs, subject to the constraints imposed by the inputs and the technology. Fare *et al*. (1989) modified Farrell's (1957) measure of technical efficiency using the nonparametric mathematical programme DEA to construct a production frontier and calculate the enhanced efficiency measure. Output quantities, rather than prices, were used and the efficiency measure could generate a variety of performance measures, depending on what is being maximized, minimized and held constant (orientation of the analysis).

Fare *et al*. (1993), followed by Hetemaki (1996), also treated environmental effects as undesirable outputs and used a distance function where the shadow prices of undesirable output are calculated from the model. Furthermore, according to Tyteca (1996) the approach could be modified to derive an environmental performance measure as the ratio between the overall productivity measure, (using both desirable and undesirable output), to the gross productivity index where undesirable output is ignored.

Ball *et al*. (1994) provided an empirical application of the DEA model in which nitrogen surplus was treated as an undesirable by-product and a variety of adjusted efficiency measures and the corresponding shadow prices of the undesirable output were calculated and used to produce a

Tornqvist productivity index for US agriculture. Their analysis highlighted the significance of including undesirable output in any analysis.

Tyteca (1996) also viewed environmental effects as undesirable outputs and, using a non-parametric approach, developed three alternative DEA models for the measurement of productive efficiency, claiming each model expanded the initial idea of DEA, i.e., minimize the ratios of weighted sums of inputs to weighted sums of desirable output. The first model was an undesirable output-orientated model, where both desirable and undesirable outputs were combined with the inputs to yield a value for environmental efficiency. Undesirable outputs are viewed as peculiar outputs which are minimized with respect to other production factors (inputs and desirable outputs). The second model minimized the ratio of the weighted sum of inputs and undesirable outputs to desirable output, while the third used a normalized undesirable output approach, where the weighted sums of the undesirable output were scaled by the desirable output. Suffice to say that the studies mentioned thus far all included three sets of factors: inputs, desirable outputs and undesirable outputs. Environmental effects were incorporated in the output vector, and the measure of technical efficiency incorporated the generation of one or more environmental effects as by-products of the production process.

Reinhard *et al*. (1999; 2002) adopted a different approach. Econometric techniques were used to obtain efficiency estimates. Using a single output, a stochastic production frontier rather than a stochastic distance function is estimated relating the environmental performance of individual farms to the best practice of environment friendly farming. Perhaps more significantly, the environmental effect, excess application of nitrogen, is modelled as a conventional input, rather than as an undesirable output. Reinhard *et al.* (1999) purport that the environmentally detrimental input can be measured but the environmental consequences cannot be measured. Undesirable outputs cannot then be incorporated in the model; hence nitrogen surplus is taken as a proxy for the environmental consequences. Focusing on just one of several inputs it is said to be an input-oriented, single factor measure of the technical efficiency of the environmentally detrimental input. It is a non-radial notion of input efficiency and allows for a differential reduction of the inputs applied compared to the standard radial measure which treats the contribution of each input to productive efficiency equally. Separate estimates of technical efficiency and environmental efficiency are provided, enabling an assessment of the compatibility of both types of efficiency.

De Koeijer *et al*. (2002) applied the non-parametric DEA to obtain estimates of technical efficiency and environmental efficiency of Dutch sugar beet growers, although they followed the approach of

Reinhard *et al*. (2002). The question of which farms are relatively technically efficient and relatively environmentally efficient and whether or not the two types of efficiency are compatible is raised. De Koeijer *et al*. (2002) claimed that it is important to account for the fact that environmental damage depends on the area over which the total damage spreads, and define environmental efficiency per unit area to take account of the carrying capacity of the environment. To minimize the observed environmental impact, an acreage constraint replaces the output maximization constraint in the technical efficiency measurement, and ensures pollution per unit is minimized while searching for efficient farms. The environmental impacts of polluting inputs, rather than the amount of observed inputs, are used to measure environmental efficiency. Area-oriented environmental efficiency (EEa) is distinguished from the conventional output-oriented environmental efficiency (EEo) and is then used as an indicator of sustainability.

With increasing appreciation of environmental benignity in production, methods of measuring environmental efficiency of agricultural production are required to inform production and policy decisions. The efficiency associated with nitrogen (N) fertilizer use in the diary industry in the Midlands of KwaZulu-Natal will be estimated through the DEA method in this study. In order to be able to measure environmental performance (or efficiency) an environmental efficiency framework needs to be constructed (Zhang, 2008). When external effects, such as environmental externalities, are attached to the use of certain inputs (often referred to as polluting inputs), these inputs represent means of reducing external impacts or the production of undesirable outputs. A similar assertion was made by Piot-Lepetit *et al*. (1997) and echoed by Zhang (2008) and this reasoning is particularly suitable for measuring the environmental efficiency in agriculture. Ensuing from the foregoing assumption was the development of a DEA framework for estimating potential reduction of environmentally detrimental inputs by Piot-lepetit *et al*. (1997). Similar DEA frameworks were previously proposed by Ball *et al*. (1994) and subsequently by Reinhard *et al*. (2000).

In keeping with the studies previously mentioned in the preceding section and supported by Zhang (2008) in the study of environmental performance in China's agricultural sector, the bad-input oriented DEA model should take three kinds of variables into consideration, viz., good inputs, output and its conventional inputs. The bad inputs pertain to the environmentally detrimental inputs such as fertilizer. Thus, the measure of environmental efficiency could be viewed as an indication of the environmental benignity of production (sometimes referred to as eco-efficiency). However, in this study the framework that will be developed and used in Chapter 8 will be largely bad-output oriented using N surplus as the bad-output (environmentally-detrimental output).

The framework that will be used in this study computes environmental efficiency through linear programming measuring performance in terms of the ability of the producer to shrink its environmentally detrimental inputs (and/or bad output, such as N balance or N emissions), given its desirable/good output and its conventional inputs (Zhang, 2008). The described linear programming problem for estimating the bad-input orientated environmental efficiency can be represented as:

$$
\begin{aligned}
& \underset{st}{F}(x, y, b) = \min \theta_i \\
& \sum_{j=1}^{J} \lambda_j y_{qj} - y_{qi} \geq 0, q = 1,\ldots,Q \\
& x_{pi} - \sum_{j=1}^{J} \lambda_j x_{pj} \geq 0, p = 1,\ldots,P \\
& \theta_i b_{wi} - \sum_{j=1}^{J} \lambda_j b_{wj} \geq 0, w = 1,\ldots,w \\
& \sum_{j-1}^{J} \lambda_j = 1 \\
& \lambda_j \geq 0, j = 1,\ldots,J
\end{aligned}
\qquad \textbf{(2.37)}
$$

where i and j=1,...,J index the observations in the sample, x_p and y_q are the good inputs and outputs of j observation, θ_i is the inverse of the distance function for observation i and b_w is bad inputs. As in any efficiency measurement, linear programming constructs the best practice possibility curve (frontier) from observations and calculates the scaling factor on bad inputs of the observation. It is important to note that the input oriented environmental efficiency is equal to θ_i for each observation i. If $\theta_i < 1$, a sample is not lying on the frontier of the production set and an improvement of performance in relation to environmental efficiency is possible for this particular sample. If $\theta_i = 1$, this indicates that no significant improvements could be made for the sample, given the current technology as reflected by the frontier of the production set.

The input-orientated environmental efficiency measure discussed can easily be adjusted into an output-orientated environmental efficiency measure. This versatility of the methodology is of importance to agricultural production, particularly the dairy industry. This is so given the dilemma of deciding whether to use an input- or output-orientated approach in measuring environmental efficiency. There are equally convincing arguments of adopting either approach: One can view environmental efficiency in dairy production either in terms of the over-use of polluting inputs, such as fertilizer and other chemicals, or as over-production of N emissions (positive N balance). In Chapter 8 the latter approach is adopted. Chapter 8 is an econometric measure of environmental efficiency based on Reinhard *et al*. (1999) and Chapter 9 is a DEA approach to measuring environmental efficiency.

2.6 Conclusion

The purpose of this chapter was to give an overview of specific production economics concepts and introduce the concepts that will be used for analyzing the data in the empirical chapters that follow. The production functions and other production economics concepts discussed in this chapter will be discussed more extensively in the results chapters before presenting the respective results. A number of textbooks give good coverage of production economics to varying degrees of complexity (for example see Call and Holahan, 1983; Beattie and Taylor, 1985; Varian, 1992; Henderson and Quandt, 1980).

In summary, the chapter began with discussing efficiency and productivity. Variation in efficiency and productivity is common in all industries, thus it is incumbent upon production economists and econometricians to develop the analytical tools and the empirical techniques needed to study it. The ability to quantify variation in efficiency and productivity and to identify its sources makes it possible to adopt private firm practices and public policies designed to improve it.

This chapter has provided motivation for the study of efficiency and productivity and the theoretical underpinnings. The basics of the underlying theory and the empirical techniques have been laid and this serves as motivation and preparation for the more extensive analyses provided in subsequent Chapters.

Chapter 3: Dairying in the Midlands, KwaZulu-Natal

3.1 Introduction

South Africa has a relatively poor resource base. Only about 15 million hectares, or 12 percent of the land area, is under cultivation, and only about 10 percent of this under irrigation. Furthermore, the climate is unstable. Generally, the best rainfall is in the Western Cape surrounding Cape Town, along the coast of KwaZulu-Natal, and in Mpumalanga. The rest of the country is relatively dry, and much of the arid Northern Cape is suitable only for grazing sheep (McKenzie, et al, 1989; Vink, 2003).

South African agriculture is of a highly dualistic nature, where a developed commercial sector co-exists with large numbers of subsistence (communal) farms. Agriculture is well diversified and it includes all the main sectors, i.e. field crops, livestock and horticulture. Agriculture in South Africa has also suffered serious effects from the chronic high inflation and debt that eroded other sectors of the economy in the two decades prior to the early 1990s. Input costs (fertilizers, machinery, etc.) rose by 10 to 20 percent in some years; farm debt had reached R17 billion in 1992, more than four times the amount owed in 1980. Farmers also had witnessed a deterioration in the terms of trade in farm products; for example, the amount of maize that had to be sold to buy a farm tractor increased from about 191 tons in 1984 to 347 tons in 1990 (OECD, 2005). Moreover, South Africa faced reduced harvests as a result of severe drought in the early 1990s, forcing the government to spend vital foreign exchange on food imports.

Under apartheid-era legislation until 1994, white farmers, who owned only 2 percent of the number of farms, controlled more than 80 percent of the arable land (OECD, 2005). White-owned farms averaged 1300 hectares in size, whereas black farms averaged 5.2 hectares. Because nearly 80 percent of the population was restricted to some 13 percent of the land, most black farmland was severely overused, leading to soil erosion and low productivity. As a result, many black farm families were supported by at least one person engaged in non-agricultural employment. The need for agrarian reform, broadening land ownership and increasing overall productivity, was one of the most serious issues facing the government in the mid-1990s as the inequities of apartheid were being reduced.

It is important to note that there has been a long history of state intervention in South African agriculture and deliberate bias toward commercial (white) farmers and neglect towards the majority (black). This was accomplished through a myriad of policies. Here only the most salient policies will be discussed. The Land Acts, the Administration Act of 1927 and many other Proclamations made in terms of these acts during the 1960s are among the most important. These policies were used to control the form of land access in the 'reserves' and the main economic ramification was to increase the transaction costs of changing land tenure forms (Vink and Kirsten, 2000; Vink, 1986; Ault and Rutman, 1993) thus locking the majority of black farmers out of the commercial sector and relegating them to being small-scale farmers.

South Africa has undergone enormous economic, social and political change since the beginning of the democratisation process in 1994. This process of reform in South African agriculture has been well-researched (e.g. Sandrey and Vink, 2007; Van Zyl *et al.,* 2001; Vink, 2003; Vink and Schirmer, 2002). A more comprehensive coverage of the reform in South African agriculture can be found in Vink (2003) and Sandrey and Vink (2007). Only a summary of this process is rendered here. The period of the 1980s was characterised by attempts to improve the efficiency and viability of the commercial farming sector, but within the confines of the then existing framework of support, and largely in the interest of fiscal sustainability. However, after the first democratic election of 1994 this changed, although in agriculture some direct policy changes had to be kept in abeyance until 1996, that is, until after the withdrawal of the National Party from the Government of National Unity (Sandrey and Vink, 2007). The most important policy initiatives taken since include trade liberalisation, land reform, institutional restructuring in the public sector, the promulgation of the Marketing of Agricultural Products Act and the Water Act, and trade policy and labour market policy reforms. The purpose of these policy reforms was to correct the injustices of past policy, principally through land reform, to get the agricultural sector on a less capital-intensive growth path, and to enhance the international competitiveness of the sector.

The overall results of the reform process have been positive with a stronger and stable macro economy, better integration into the global trading system, and progress in redressing past injustices and reducing poverty. There are still many challenges facing the government and South African society as a whole, including widespread unemployment and poverty, a large unskilled workforce excluded from the formal economy, weak social and educational systems, and a significant level of crime and a high prevalence of HIV/AIDS (OECD, 2005).

Agriculture contributes less than 4 percent to Gross Domestic Product (GDP) but accounts for almost 10 percent of total reported employment and 8 percent of exports. The sector is increasingly export oriented with about one-third of total production exported. The conditions for agricultural production are not favourable in most regions (90 percent of high potential land is in KwaZulu-Natal and Mpumalanga) due to poor land quality, highly variable climatic conditions and a scarcity of water.

The commercial agricultural sector adapted well to the policy reforms and liberalisation efforts. However, economic and financial pressure on commercial agriculture is substantial, and as with other sectors, farmers must adapt their production and investment decisions to the market situation and overall economic developments. These market pressures need to be considered in the context of land reform and Black Economic Empowerment (BEE). The new entrants into commercial agriculture (and into agricultural based services) are at a considerable disadvantage relative to the more experienced operators in responding to these challenges.

Continued land reform is one of the most important agricultural policy challenges, in particular how to improve the land acquisition and resettlement process and create stakeholder consensus around the implementation strategy.

Facilitating economic integration between small and large-scale commercial units is another policy challenge. The ability of the commercial sector to respond to increased market opportunities will ultimately determine any gains from global trade liberalisation. Farming policies need to be conducive to the adoption of quality and productivity improvements for this sector to become more internationally competitive and exploit its export potential.

Soon after the formation of a democratic government, it became apparent that the dualism in South African agriculture had to be addressed. The new government embarked on a land reform programme soon after 1994 (LRAD, 2000). More recently, the debate has shifted from planning to the implementation of the land reform programme. Some of the more important studies in this regard include Department of Land Affairs (1997); Hall (2004); Kirsten *et al.* (2000) and Graham and Lyne (1999). The last three references are particularly interesting as they show empirically the slow pace of land transfer.

In South Africa, a pilot land reform programme was designed, more or less in accordance with the guidelines of the market-assisted approach. In practice, however, beneficiary households usually had to pool their meagre grants in order to buy land from a willing seller. A more comprehensive coverage of this pilot project is rendered in Vink (2003). The reason was at least partly due to the fact that the Subdivision of Agricultural Land Act (Act 70 of 1970) has yet to be repealed, which would have enabled the sub-division of farms into affordable pieces of land.

There is general consensus that this pilot land reform programme has not been largely successful largely because farms financed with land grants and settled by groups of households were too small to support all of the beneficiaries as full-time farmers (Department of Land Affairs, 1997). The assumption by the Department of Land Affairs was that farmers that received grants from the government would be able to leverage loans from commercial banks. However, most creditworthy farmers did not qualify for a land grant as the means test applied to potential beneficiaries precluded individuals with a monthly household income greater than R1 500 (Graham and Lyne, 1999).

Given the little success of the pilot programme, a new approach to land reform has been adopted after extensive consultation and planning. In providing for an extended scale of grants, dependent on an increasing own contribution, it fits directly with the new vision of the Ministry to benefit the rural poor and to assist in the establishment of a class of commercial black farmers. This initiative will, however, also fail unless efforts to implement the programme are well planned and well co-ordinated, unless support services for agriculture, i.e. research, extension, finance, information, infrastructure are in place to provide the conducive environment for a vibrant and successful agricultural sector, and unless the problem of bureaucratic centralisation is addressed (Vink, 2003).

The net effect of the land reform programme has had limited success as can be seen by the fact that only about 1 million ha of the available agricultural land in South Africa that has been transferred through the formal programme.

3.2 The dairy industry

The dairy industry is the fourth largest agricultural industry in South Africa, representing 7.5 percent of the gross value of all agricultural production in 2007/08 (DAFF, 2009). The gross value of milk produced during the 2007/08 production season (March-February), including milk that was produced for own consumption on farms, was estimated at R9 billion. More than 65 percent of dairy products are distributed through hypermarkets, supermarkets and superettes (WESGRO, 2004). The dairy industry is also important to the South African economy through employment. The approximately 4 300 milk producers directly employ about 60 000 farm-workers and indirectly provides jobs to some 40 000 people (South Africa Online, 2006).

South Africa has produced between 2.3 and 2.5 billion litres of milk annually since the mid-1990s (DAFF, 2009). More than 64 percent of the milk is produced in the Western Cape, Eastern Cape and KwaZulu-Natal on pasture based systems, with KwaZulu-Natal producing 21.1 percent, equivalent to 500 million litres (MPO, 2007). In addition to South Africa's own production, 4.5 million litres of milk and 9.9 million n kg of concentrated milk and powdered milk were imported in 2007 (MPO, 2007). There was a reduction of 2 percent on the total milk to market from 2006 to 2007, largely because of a drought in the summer rainfall area, which resulted in less silage being produced, and the high prices of maize and other grains (MPO, 2008). This is an indication that there is capacity to expand within the country.

3.2.1 The dairy supply chain

In order to understand the dairy business in South Africa, it is important to have insights to the overall demand and supply relationships, price trends and net imports (supply chain). The dairy supply chain in South Africa is complex. The supply chain can be considered to start at raw milk production and to end when other processors, institutions and final consumers utilize products that were created in the value chain. The different markets and marketing channels for milk are indicated in Figure 7, albeit in simplified form. Figure 7 shows that there are different marketing possibilities open to the South African dairy farmer. The farmer can sell directly to the consumer; sell to a retailer (e.g. supermarket); sell to processors and/or distributors (e.g. Clover); or process and sell to retailer and consumer. The dairy farmer can use any of these marketing channels. However, the majority of farmers in the KwaZulu-Natal Midlands sell their milk to the processors/distributors. Private expenditure on dairy products was estimated at R8 374 million for the same period, an amount that includes the purchase of imported dairy products (Table 1).

Table 1: Dairy supply chain: values attached to different activities (2001/2002)

Category	Rand (million)
Production of raw milk	
Direct inputs	3 017
Infrastructure	9 249
Raw milk sold	3 899
Secondary market	
Imports	315
Exports	302
Expenditure on intermediaries	6 278
Expenditure on infrastructure	NA
Private expenditure	8 374

Sources: NDA, 2002; SAMFED, 2001

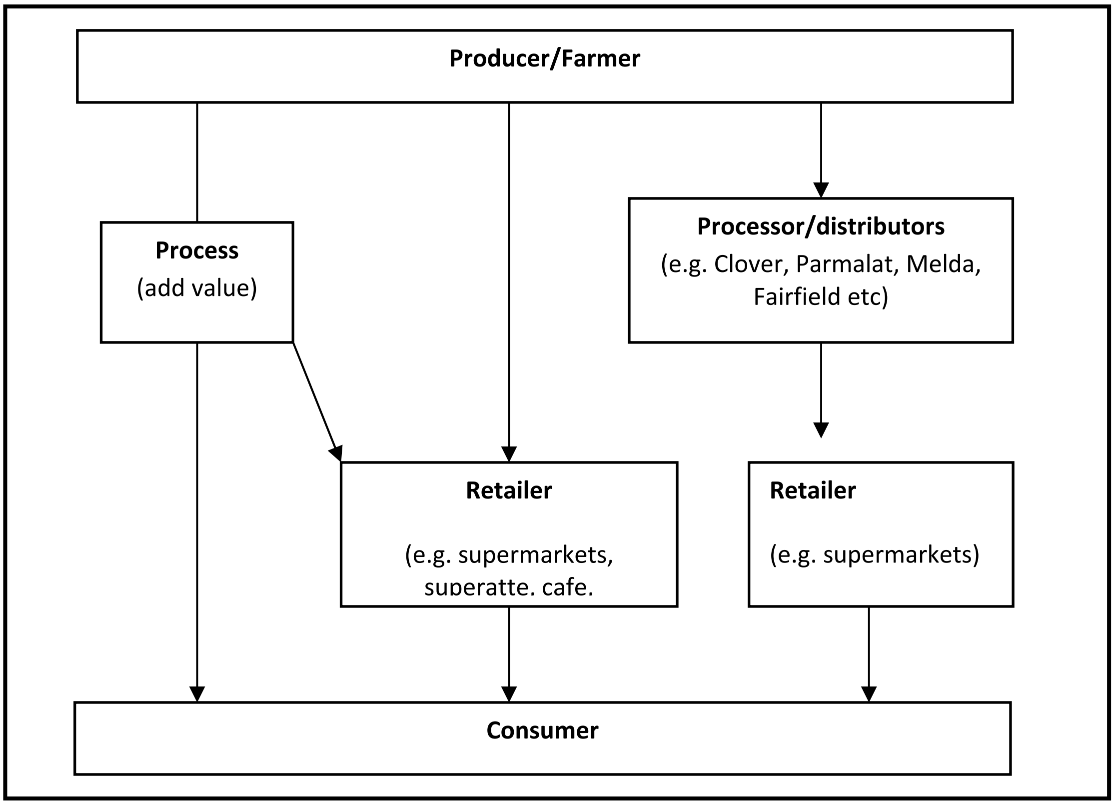


Figure 7: Simplified marketing channels for milk and milk products

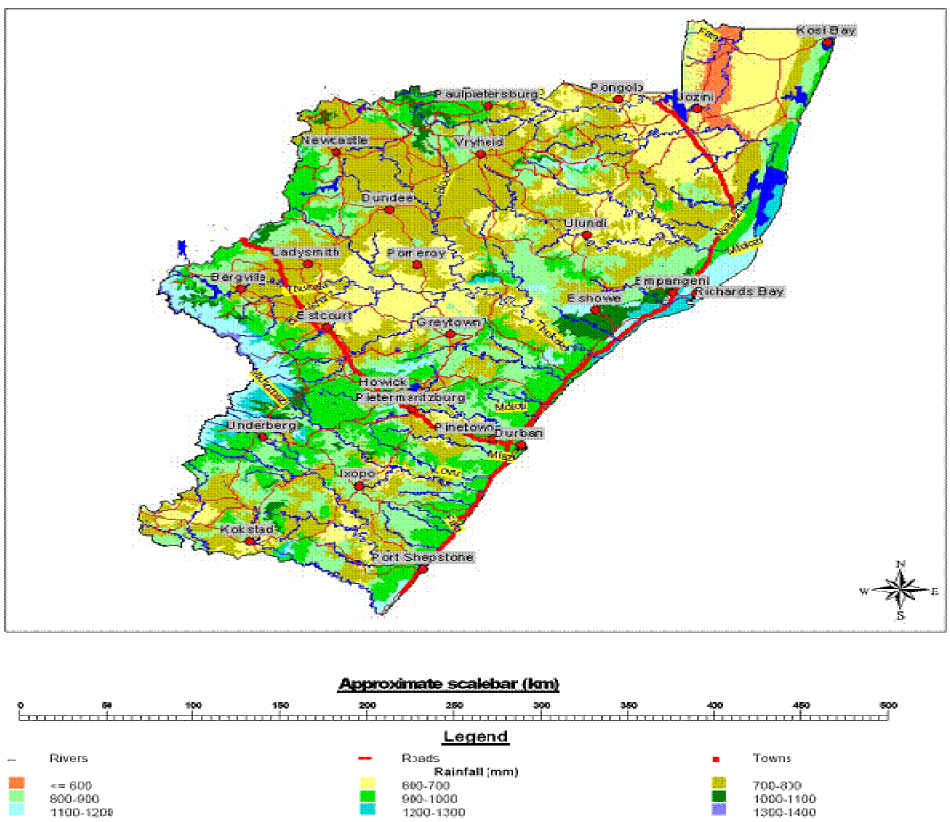
3.2.2 Performance trends

The total number of fresh milk producers in South Africa declined from 5 348 at the end of 2001 to 3 665 by January 2008 (MPO, 2008). The number of producers per province is shown in Table 2. Since 1997, the number of producers has decreased by 48 percent. The largest decrease occurred in the Northern Cape (74.4%), while the Free State has the lowest decrease in the number of producers (23.7%). An intensive campaign of producer registration has contributed to the low decrease in numbers in the Free State (MPO, 2003). The trend towards higher production in the pasture-based areas (coastal areas, Western Cape, KwaZulu-Natal and Eastern Cape provinces) is continuing. Figure 8 shows the concentration of milk production per district in the provinces. The study area (KwaZulu-Natal Midlands- from Howick to Ixopo – see Figure 8) falls between the 50.1-120 litres km^{-2} to 120.1-200 litres km^{-2} milk production density areas as shown in Figure 9.

Table 2: The number of producers per province, 1997 to 2009

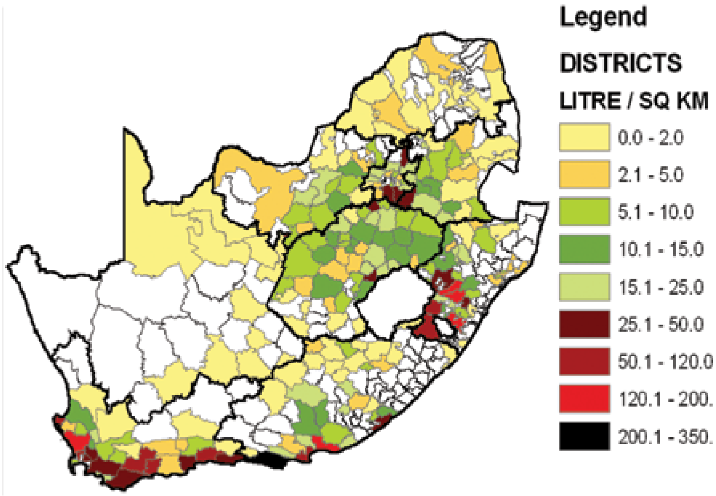
Province	*Number of producers*					*% Change 1997-2010*
	1997	**2006**	**2007**	**2008**	**2010**	
Western Cape	1 577	878	827	815	754	-52.19
Eastern Cape	717	422	420	407	354	-50.63
Northern Cape	133	39	37	34	45	-66.17
KwaZulu-Natal	648	402	385	373	348	-46.30
Free State	1 204	1067	987	919	835	-30.65
Northwest	1 502	649	596	549	507	-66.25
Gauteng	356	275	245	228	212	-40.45
Mpumalanga	866	407	357	302	248	-71.36
Northern Province	74	45	45	38	29	-60.81
Total	**7 916**	**4 184**	**3 899**	**3 665**	**3 332**	-57.91

Adapted from: MPO statistics



Source: Bioresource Unit, KwaZulu-Natal Department of Agriculture

Figure 8: Total rainfall map for KwaZulu-Natal



Source: MPO statutory survey; LACTODATA, 2008.

Figure 9: Milk production density (litre/km²) per district, 2006

Interestingly, production of milk per producer has been increasing on average (MPO, 2003; Coetzee, 2002). Average milk production per cow per day was 15.2 litres in 2006. The MPO (2008) estimate that 89 percent of the total milk produced in 2006 was sold in the formal market and three percent was sold informally. The balance of the milk produced (8%) was used for own consumption and for feeding calves on the farm. Although production per producer has increased, costs of production have also increased (by an average 44 percent from 2001 to 2003 (MPO, 2003)) and the trend is still persisting. For the majority of dairy farmers in KwaZulu-Natal, the highest cost items in milk production are feed and labour (MPO, 2003; Coetzee, 2002; Gordijn, 1985). The efficient use of all factors of production will result in efficient production and profit maximization. However, even a small reduction in feed and labour cost would result in significant improvement in the profitability of dairy farms in KwaZulu-Natal (Coetzee, 2002).

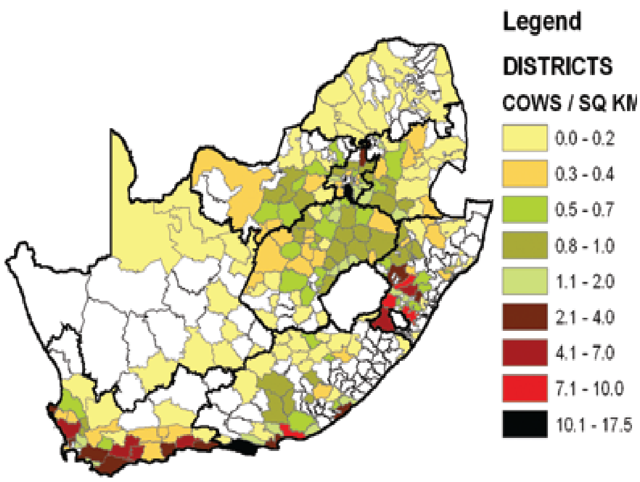
The geographical distribution of milk production is shown in Table 3. There has been a clear movement of milk production from the inland to the coastal (KwaZulu-Natal, Western Cape and Eastern Cape) areas in the country. Milk production in the coastal areas increased from 52 percent to 62 percent of the total between 1995 and 2000.

Table 3: Geographical distribution of milk production, 1997 and 2007

Province	Percentage of production	
	1997	2007
Western Cape	22.9	25.3
Eastern Cape	13.8	21.8
Northern Cape	1.2	0.7
KwaZulu-Natal	15.7	21.1
Free State	18.0	12.8
Northwest	12.6	7.1
Gauteng	4.4	3.1
Mpumalanga	11.0	7.6
Limpopo	0.4	0.5
Coastal areas	**52.4**	**68.2**
Inland areas	**47.7**	**31.8**
Total	**100**	**100**

Source: MPO (2008) estimate; Own calculations

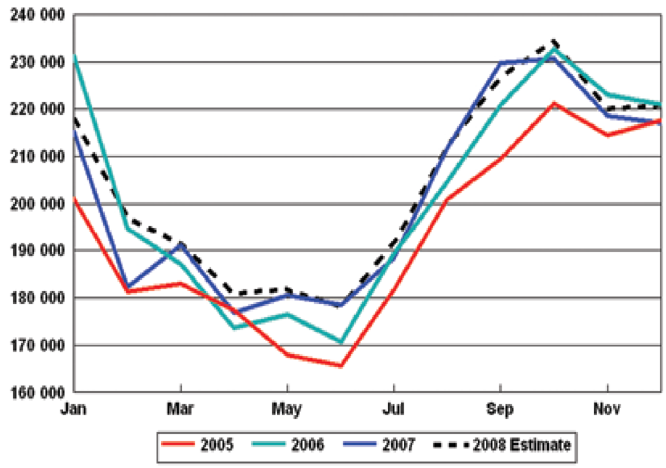
Figure 10 shows the concentration of cows per district. There are a number of possible reasons for this spatial concentration of dairy farms along the coastal areas of South Africa. One reason is that these coastal areas are within close proximity to viable ports and this tends to lower transportation costs of imported inputs relative to more inland areas. Another reason could be that the coastal areas are more suitable because of mild temperatures and good rainfall and these climatic factors assure good-quality natural and cultivated pastures (Republic of South Africa, Department: Agriculture, 2003; 54). Unfortunately the major market for dairy products lies in the inland areas (Coetzee, 2002).



Source: MPO statutory survey

Figure 10: Cow density per district (cows km^{-2}), 2006

Milk production in South Africa shows a seasonal pattern with a peak in December and low production in winter. The seasonal production pattern is depicted in Figure 11. Not only does the production and consumption of milk in South Africa exhibit seasonality but it also varies from year to year, although the overall trend displays an increase over the year. Another important factor to note is that milk consumption has been steadily increasing over the years. A marked increase in consumption of dairy production emerged from 1992 (Dairy Marketing, undated). Figure 12 shows the production and consumption of milk in South Africa from 2004 to 2008. Interestingly, until about 2004, the local consumption of milk never exceeded the production but this began to change from 2005 onward, creating a deficit instead of a surplus in milk in the country.

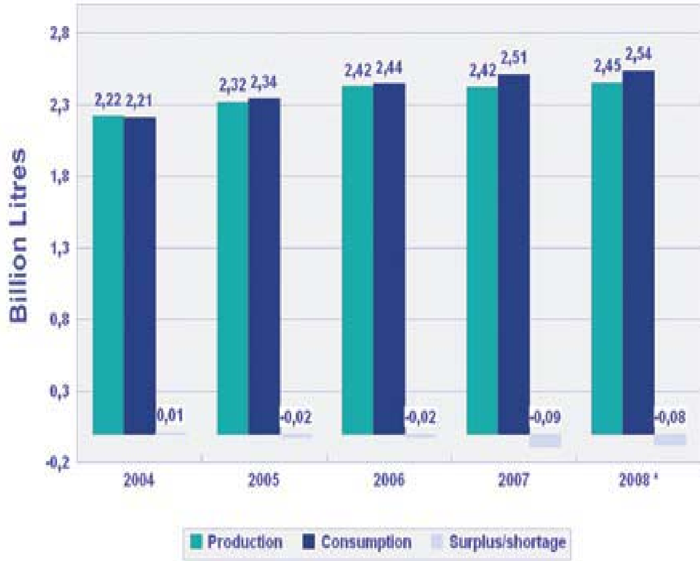


Source: MPO calculation (adapted from LACTODATA, 2008)

Figure 11: South African seasonal milk production

It is believed that the increase in milk consumption is a result of a growing middle class and higher per capita disposable income. A combination of the afore-mentioned two factors results in increased demand for milk (both a movement along the demand curve to the right and shift of the demand curve- expansion). Furthermore, a reduction in the rate of growth of consumer expenditure on durable goods and moderate retail price increases for dairy products during 2007, added to the growth of demand for dairy products. It is worth noting that the demand of milk is also cyclical, with higher demand in the early summer.

Theoretically prices are formed as a result of market demand and supply. When there is a shortage of milk, prices increase. Farmers then produce more milk at the higher producer prices and a surplus develops, with a subsequent decrease in producer prices. Producer prices showed an increasing trend from March 1999 because of a shortage of milk (Dairy Marketing, undated). However, this did not result in any corresponding increase in production because producers were still suffering from the combined effects of declining producer prices and higher interest rates during the previous two years. Due to the nature of dairying, producers can only absorb lower producer prices for only a short period of time. If milk prices decline to a level lower than variable cost and remain at that level for a long time, this will invariably lead to the liquidation of dairy herds.



Source: MPO (2008)

Figure 12: Annual milk production[4] and consumption, 2004 to 2008[5]

Although the variable cost of producing milk from pastures in the coastal areas is lower, the extra cost to transport milk from coastal areas to the markets should be taken into account. Despite the fact that the variable cost of producing milk from pastures is lower in the coastal areas, there are still dairy farmers that are less efficient in their milk production, and are thus struggling to break even. It is this dichotomy in production efficiency in the KwaZulu-Natal dairy industry that is of particular interest and begs research to establish the determinants of technical, economic, and environmental efficiencies.

The size distribution of milk producers for South Africa as a whole is shown in Table 4. The number of smaller milk producers is declining while the share of larger producers in total milk production is growing. Average milk production per cow per day was 17.3 litres in 2009, five percent increase compared to the previous year (MPO, 2009; 2010). Given the current trend of fewer and larger farms surviving, it is likely that there are increasing returns to scale which need to be taken into consideration in modelling efficiency in the dairy industry.

[4] Excludes milk retained on farm
[5] 2008 figures are estimates and are based on MPO forecast

Table 4: Size distribution of milk producers, 1995 and 2001

Daily production (litre/day)	Percentage of producers		Percentage of production	
	1995	2001	1995	2001
0 – 500	58	45	19	9
501 – 1 000	21	17	20	9
1 001 – 2 000	13	17	24	19
2 001 – 4 000	6	11	22	24
4 001 – 6 000	2	5	5	15
> 6 000	0	5	10	24

Source: MPO, 2008

Table 5 shows the average number of cows-in-milk per producer in 2006 for each province: dairy farms in the coastal areas have the highest number of cows-in-milk compared to their inland counterparts. Declining real (inflation-corrected) farm-gate returns for milk are an ongoing challenge to dairy farm business viability. Returns, generally, are declining in the industry as inflation increases the cost of farm inputs, new technology reduces the cost of production of substitutes and competition provides consumers access to better value or substitute products from other farmers (Coetzee, 2002).

The effect of lower real output prices and increased costs is known as the "price-cost squeeze" and is not unique to dairy farming. The decline in the value of the rand (ZAR) in the early part of this decade was one of the main causes of input price increases. The hypodissertation is that dairy farmers in KwaZulu-Natal can survive and remain profitable under current economic circumstances.

Table 5: Number of cows-in-milk per producer, 2009

Province	Number of cows	
	Mean	Median
Western Cape	203	150
Eastern Cape	468	313
Northern Cape	141	100
KwaZulu-Natal	367	310
Free State	113	82
North West	96	77
Gauteng	99	62
Mpumalanga	116	88
Limpopo	175	71
South Africa	**209**	**145**

Source: MPO, 2010.

The dairy farmer is currently caught in a price-cost squeeze and as a result it is imperative that the farmer be familiar with the expenses associated with the farming business. Other industries can set the selling price of their commodity, yet in the dairy industry the only means of increasing profits in the short-run is to maintain production and reduce input costs (MPO, 2003; Gordijn, 1985). Although the dairy marketing board was abolished years ago, farmers supplying their milk to processors still operate under some sort of quota system in that they enter into a contract with the processor to supply a given quantity and quality (butterfat content) of milk. Failure on the farmer's part to meet contractual obligations incurs penalties from the buyer in the form of lower buying price per litre. The survival of the dairy farmer therefore hinges on the farmer becoming cost efficient and having more business acumen. It is worth noting that the farmer can produce as much milk as possible even though an increase in milk produced may have a dampening effect on the milk price at the farm gate.

3.2.3 The policy environment in the South Africa dairy industry

Many agricultural products in South Africa have gone full circle from absolute control to a free market, and the dairy supply chain is no exception. The dairy supply chain was historically controlled and regulated by means of the Dairy Industry Control Act of 1961, the Marketing Act of 1968, various Dairy and Milk Boards, national, provincial and local health legislation, plus a variety of other acts and regulations. In 1930, Act No. 35 was enacted which led to the establishment of the Dairy Industry Control Board. The Board was re-established in 1939 under the terms of the Marketing Act of 1937. Under the Marketing Act of 1937 dispensation, the Dairy Board had the exclusive right to sell milk and fixed prices were paid to the primary producers of milk. The prices were fixed by the Minister of Agriculture and were adjusted periodically after consultation with the Dairy Board. A surfeit of control measures were in place that regulated the South African dairy supply chain. The plethora of control measures included, amongst others, health issues in production and processing of raw milk and the fixing of margins during the different processing phases until it landed as an end product with fixed prices or fixed margins in the retail outlets (NAMC, 2001). Only salient changes will be highlighted here as these will help put the structural changes in the dairy supply chain affecting its costs and the end price into perspective.

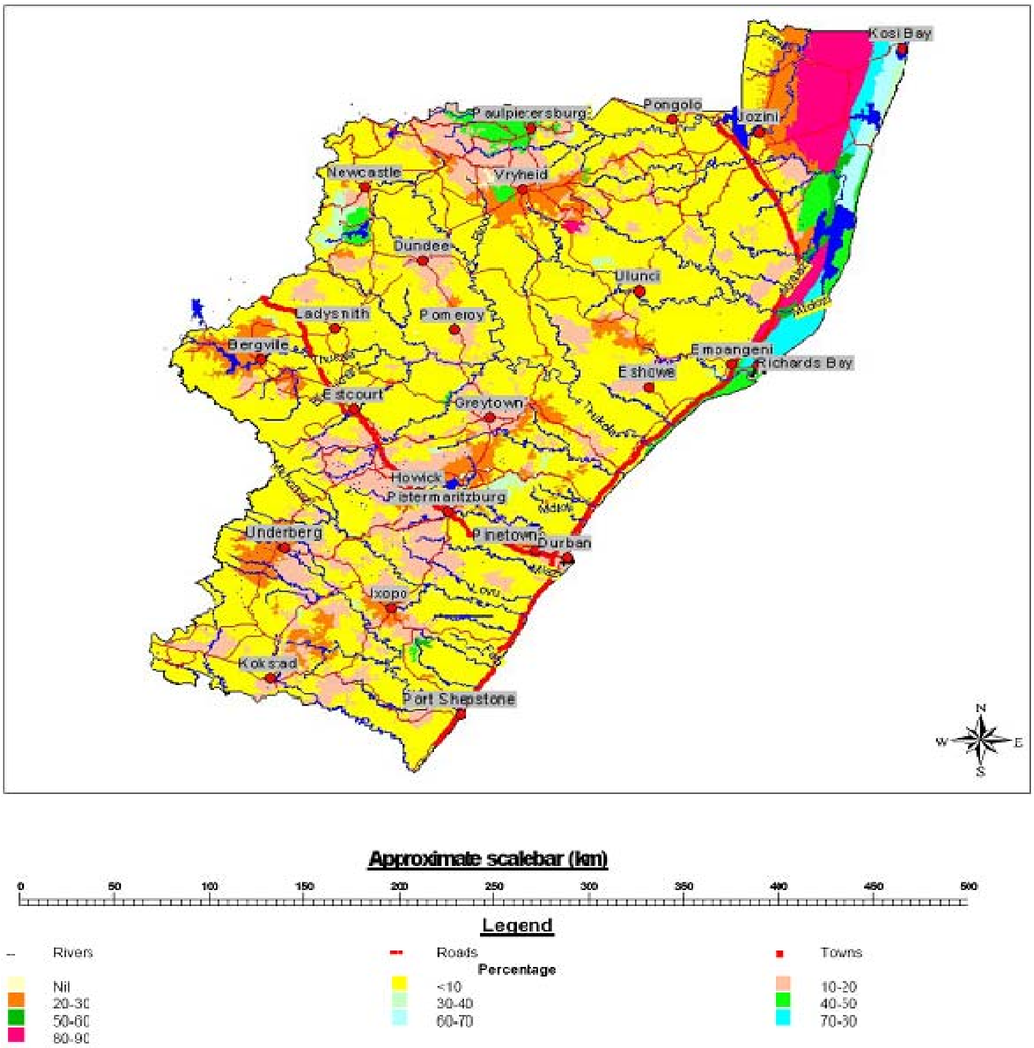
In 1971 Government allowed margarine to be coloured yellow. This resulted in a drop in annual butter sales from more than 54 000 tons in 1971 to 16 000 tons in 1979 (NAMC, 2001:22), and changed the face of the industry. However, statutory intervention in the dairy industry has gradually been removed since 1982. The retail price control of fresh milk was abolished in July 1982; the retail price control of butter and cheese was abolished in 1985. The Dairy Industry Control Act was abolished in 1987. The final deregulation steps followed during the Uruguay Round of the General Agreement on Tariffs and Trade in 1994 when quantitative import control was replaced by import levies. This deregulation resulted in the Dairy Scheme being rescinded as from 1 January 1994 as demonstrated by the demise of the Dairy Board and its activities on 31 December 1993. The new milk scheme was promulgated on 24 December 1993 and the Milk Board and Milk Producers Organisation (MPO) started functioning on 1 January 1994. The deregulation had the important effect of increasing legal and illegal imports (NAMC, 2001: 26-27).

3.3 The KwaZulu-Natal dairy industry

There are 381 milk producers registered with the milk producers' organization of KwaZulu-Natal (KZNMPO) at present, dramatically lower than the 648 of 1997 (MPO, 2007). This is an indication of the small margins to be made out of dairying, with fewer producers producing a lot more milk from more cows to stay economically viable. Of the milk producers in KwaZulu-Natal one from a previously disadvantaged background is registered with the KZNMPO, four with the National milk recording scheme and an estimated 20 other producers in the informal market.

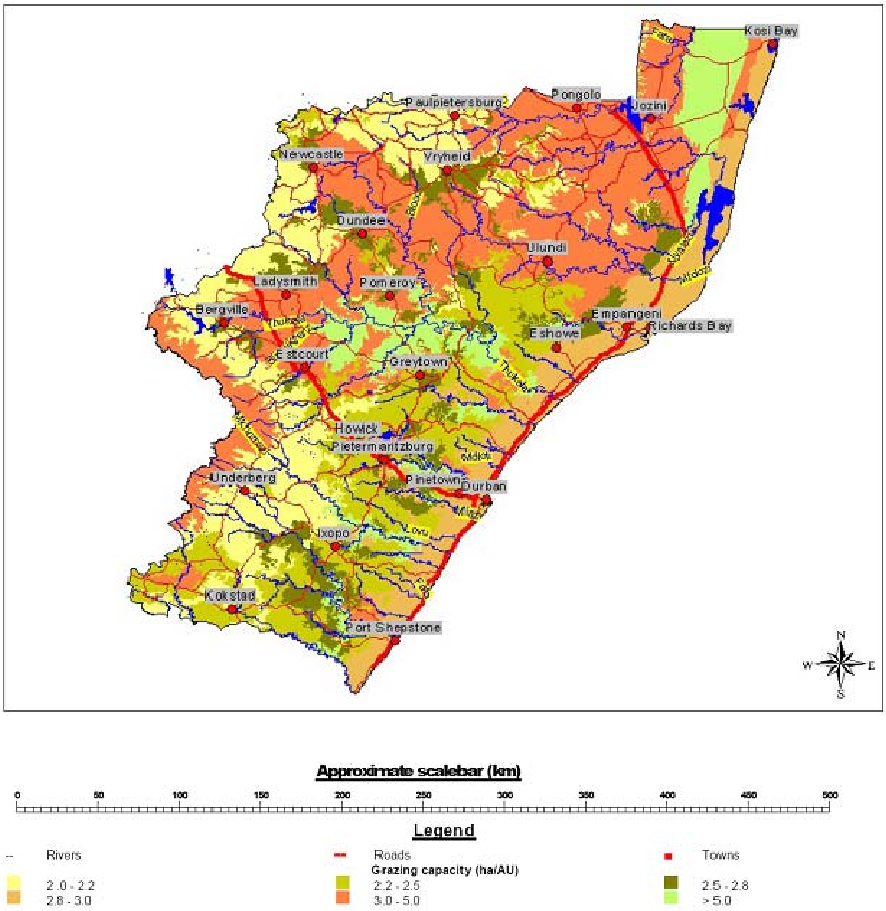
Most farms within the Midlands of KwaZulu-Natal are predominantly grazing farms, mostly irrigated ryegrass (predominantly annual ryegrass, but some perennial ryegrass) and dryland kikuyu, with maize silage and hay (*Eragrostis curvula* or veld) being fed at strategic times. Dairy meal is fed at the rate of an average of 6.5 to 7.5 kg per cow-in-milk daily, ranging from zero to 10 kg of meal per head daily (Penderis & Penderis, 2004).

Within KwaZulu-Natal most of the milk is produced in the Mooi River, Howick, Boston, Bulwer, Underburg, and Ixopo areas, all within the Midlands region (see Figures 13 and 14), making it the most important milk producing region in the province. Interestingly the sample for this study falls within this region, from Ixopo, down South, to the Mooi River area, further north. The long-term rainfall average of the Midlands ranges between 800 to 1000 mm per annum. This amount of rainfall is more than adequate for good pasture growth in the rainy season (summer). This concentration of dairy farms in the Midlands is due to more conducive climatic and soil conditions (Figure 13), lower temperatures and higher rainfall (Figure 8) which promotes the growth of kikuyu in summer and ryegrass under irrigation in winter making the region suitable for quality grazing. In Figure 13 it can be seen that all the areas of interest to this study have at least 10 percent arable land. Figure 14 shows that the sample area falls between 2.2 to 2.5 hectares of grazing per animal unit (ha/AU) and this carrying capacity is considered adequate for dairy farming. The Northern areas of the province (Zululand) are net importers of milk within the province and due to transport costs tend to have higher retail milk prices. This limited dairy farming is due to climatic conditions in the hot Northern areas which are not conducive to dairying, heat stress being a problem with most dairy breeds.



Source: Bioresource Unit, KwaZulu-Natal Department of Agriculture

Figure 8: KZN high potential arable soil (as a percentage of bioresource unit- bru)



Source: Bioresource Unit, KwaZulu-Natal Department of Agriculture

Figure 9: Grazing capacity (ha/au) in KwaZulu-Natal

Since the deregulation of the industry, there has been substantial restructuring of both the dairy production and processing sectors in an effort to improve global competitiveness. A significant confidence indicator in the restructuring of the processing sector, in particular, has been the substantive investment of multinationals such as Parmalat and Clover/Danone in large South African dairy companies, and the continuing presence of Nestlé.

The current chapter discussed broadly the South African agricultural sector and located the dairy industry within the agriculture economic sector outlining its contribution to employment, gross domestic product and current trends, among others. The deregulation process was also discussed in detail. Lastly, the dairy industry in KwaZulu-Natal was discussed specifically because the group of farmers that were studied come from this province in South Africa. Chapter 5 deals with the subject of modelling efficiency of production of the dairy farms. The information on the dairy industry in the KwaZulu-Natal Midlands suggests that farmers are constrained as to how much to supply and if this is so then an input orientated model would be appropriate. However, dairy farms are getting fewer and bigger every year and it would be interesting to find if farms are get bigger due to increasing returns to scale or some other factors. The following chapters will attempt to shed some light to these questions.

Chapter 4: Modelling the efficiency of dairy farms

4.1 Net and gross output and input approaches

In the national income accounts for agriculture, most countries include an analysis of total factor productivity for the national farm. The best developed example is perhaps that for the US, which has been copied for the United Kingdom and for South Africa by Thirtle *et al*. (1993). The approach taken is to work in terms of net outputs and inputs. The key concept is that when an input purchased off the farm crosses the farm gate it is recorded on the input or negative side of the balance sheet. Outputs on the positive side of the balance sheet are only recorded when the product leaves the farm to enter the rest of the economy. The point is that if an input such as animal feed is produced on the farm and consumed by farm animals it is the milk or meat resulting from the animal that is recorded as an output. The farm produced input is usually not measured at all. If it were, an alternative approach could be taken and the accounts worked on the basis of gross outputs and inputs. This is the approach towards which the EU farm accounting schemes are moving. If the gross basis is used, then farm produced feed would be recorded both as an input and as an output. It is exactly because it appears on both sides of the balance sheet that it can be subtracted from both sides without causing any error. This makes the accounts simpler by removing several items that are hard to measure because they are produced and consumed on the farm. The choice of how to model efficiency in agriculture continues to be a difficult one because of these measurement issues and one that has been tackled before. Dovring (1977) dealing with the issue of whether to use gross or net productivity concluded that the choice should be informed by available data and the industry under consideration. Dovring (1977) concluded that this was a problem of aggregation.

In this analysis of dairying, these concepts can be applied to show the different models that result. The purchased inputs in the net approach are as follows:

- Basic inputs – land and labour
- Intermediate inputs – veterinary services and medicines, and purchased feed
- Capital inputs – running costs of milking machinery, and other machinery and inputs
- Outputs - milk, surplus feed and other crops produced and sold, meat animals

Figure 15 shows a conceptual model of the relationships between these variables.

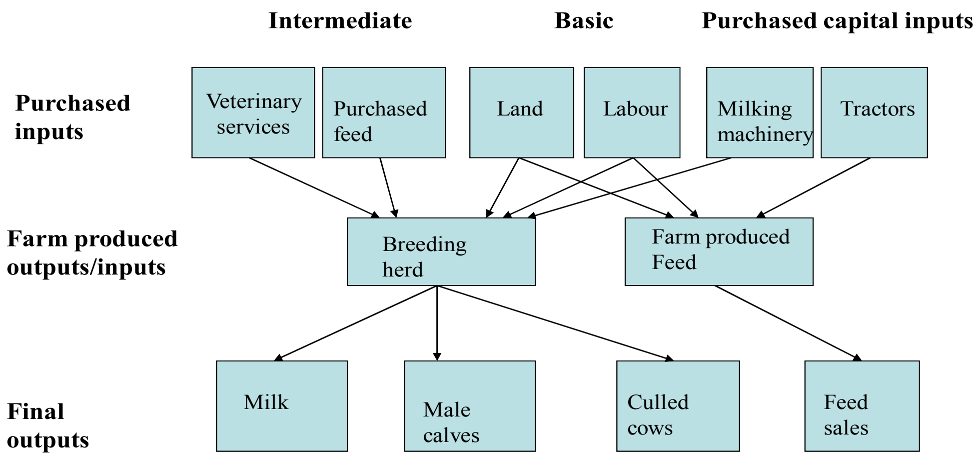


Figure 10: Dairy farming: a conceptual model

Milk or butterfat is the main output, accounting for as much as 90% of the total value. However, most farms have an 'other outputs' category, which is the feed not used on the farm and hence disposed of by selling elsewhere. There may also be other subsidiary crop outputs. Note that the majority of the feed produced would not be counted under this net output scheme as it is fed to the dairy herd and does not leave the farm.

The meat animals sold fall into two distinct categories. A major function of the farm inputs listed above is to produce and maintain the dairy herd from which the milk is obtained. When heifers are bought in, the cost is subtracted from the output category called trading income, but generally the whole herd is a farm produced capital good. Again, all this production is not counted if the calculations are on a net basis. All that is counted in trading income is the value of the bull calves sold to ranching enterprises and the cull value of cows at the age of about twelve when they reach the end of their productive life. These are sold as low grade meat or enter the informal market to be used as lobola (dowry for the bride in African weddings).

The difference between the gross and net basis for the calculations is quite clear. The net calculations include the six inputs and three outputs listed above. If the accounting system were to work in gross input and output terms then farm produced feed consumed on the farm has to appear on both the input and output sides of the accounts and similarly the entire herd should appear as both inputs and outputs, rather than just the two classes of animals currently treated as output.

There is a second convention that should be observed if the calculations are to be accurate. Since all the data are recorded on an annual basis, if an input or output crosses the boundary from one reporting year to the next, this should be taken into account. Thus, it will transpire that veterinary services and other machinery have a greater impact on output during the following year rather than in the year of their use. Therefore, these two variables are lagged one period and so is farm produced feed. The herd, which is an animal capital stock, clearly presents a far greater problem in that an animal joining the herd in year t will continue until about year t+12. Note though that where a barn could be produced using farm inputs in year t and would provide services for many years thereafter, cows in a dairy herd require minding and attention throughout their lives.

Of the questions of which approach to follow there is not one that can be answered in theoretical terms. The net approach has the advantage of being simpler and less subject to errors regarding farm produced outputs that are also inputs. However, there is something unsatisfactory about not including the size of the dairy herd as an input into the production of milk. Thus, although including the herd as an input constitutes double counting unless it is also included as an output it may be preferable to take this pragmatic step in the modelling. All of these issues will be addressed in the process of estimation and interpretation that follows in the next chapter.

4.2 Summary of the operating environment for the dairy industry in South Africa

One of the characteristics of the dairy industry is its instability. This is largely a result of the extensive nature of dairy farming in the country which, in turn, is closely linked with the ecological differences between regions and the remarkable variations in the average annual rainfall and the consequent seasonal fluctuations. All these attendant factors predisposes dairy farming to be a complex enterprise thus placing high demands on advanced technology and efficiency on the part of the farmer. Thus skilled and well trained workers are essential. Not only is an intimate knowledge of dairy cattle and their management necessary, but highly sophisticated equipment is used for milking as well as providing the milking cow with the kind of nutrition that will allow her to produce the optimum amount of quality milk. Furthermore, dairy farming is a business and without the relevant business skills, a dairy enterprise is doomed. Apart from the high demand for skilled personnel, the fact that cows must be milked throughout the year twice a day requires great dedication.

4.3 The dairy financial management sample

The data used in this study were obtained from Alan Penderis of Tammac Consulting cc, a consultancy firm located in Ixopo (southern KwaZulu-Natal) which assists dairy farmers in the Midlands with production and marketing services. The farms that were selected are highly specialised dairy producers deriving more than 90 percent of their income from dairying. The dataset is comprised of 37 dairy farms within the KwaZulu-Natal Midlands area, representing approximately 10 percent of the number of dairy farms in the area in 2007 (381 farms). The farms were located throughout the study area from Ixopo up to the Mooiriver area (see Figure 8). The farms studied were of different sizes including the small, medium and large farms in the KwaZulu-Natal Midlands hence representative of the parent population.

The data cover dairy financial management data for a maximum of 37 farms for the nine years from 1999 to 2007. If it were a balanced panel it would comprise 333 observations, but there are only 25 farms for the first two years. Then the sample was increased to 37, but one farm dropped out in 2006 and only 22 farms had reported for 2007 at the point in time when the data were handed over. This gives an unbalanced panel with a total of 293 observations. The original data are all in terms of current prices, which does not allow for comparisons across time. The current price data is used first, to investigate the cross sections for the individual years, as using deflators is bound to introduce some amount of random error, but then the variables all need to be transformed to constant prices. The deflators are explained below, after the variables have been discussed.

4.4 Variables used in the basic analysis of production

The variables used in the analysis of dairy production are a small subset of the data supplied. Figure 15 is a graphical representation of a dairy enterprise and the activities involved in running a dairy farm in the sample area. The production functions explain a single output with all the important inputs. The outputs thus have to be aggregated and so do the inputs, as there are far too many to include and they tend to be collinear. The farms sell milk (**product income),** other milk products and some farm produced fodder (**other income)**, but they also buy and sell animals (**trading income)**, so these are the three components of the output variable. The variable **product income** is the net income from all milk sold, including cash sales (milk sold informally), after deducting transport charges, all levies and monthly shares deductions. The price that farmers normally receive from processors depends on a number of milk characteristics and these include butterfat and protein content and somatic cell count. Price differences between farmers are, therefore, the result of milk quality and component composition. Thus, using revenues for total output provides additional information. **Other income** includes bags sold; levies repaid; dividend and bonus received; surplus grain sales; grazing let; land lease income. **Trading income**, by definition, is gross income (inclusive of levies, transport etc) for the sale of cull cows, breeding cows, heifers, bull calves and oxen. Cattle purchases and hire purchase (charges for purchase) redemption for cattle purchases are entered in parendissertation (as a negative value) next to the cattle sales figures.

Inputs begin with the original factors of production, which are **land** in hectares and **labour** which is measured both as a physical quantity, as number of workers and as a cost, when measured by the wage bill. The cost of labour includes wages, cost of rations given to the workers, and other labour costs (for example, medical expenses, clothing, workers' compensation and Unemployment Insurance Fund (UIF)). The cost approach is generally preferable as it does quality adjust the labour input. The first intermediate input is **total feed**, which has both purchased and farm produced components. Purchased feed is the aggregate of feed bought for cows, heifers and calves. The farm produced feed is not actually measured by purchased feed and is accounted for by aggregating the inputs used to produce it. These inputs for farm-produced feed include items such as fertiliser, seed, herbicides and pesticides, and transport from source to the field. Land has already been counted, so the intermediate inputs of seed, fertiliser, herbicides, pesticides and other costs (including transport) are included here. The other intermediate input is **total veterinary cost**, which is made up of the cost of veterinary visits, medicines, artificial insemination costs, dips, semen purchases, milk recording charges and other miscellaneous costs (these include semen flasks, artificial vaginas, surgical gloves, sheaths and semen straws).

The capital inputs always present more of a problem. Since the inputs of land, labour and intermediate inputs are flows per unit of time, while capital items are stocks, the service flows emanating from the capital stocks should be calculated. These are the depreciation on the capital stocks plus the running costs. The data includes investment expenditures on capital items but does not give information that allows the capital stocks to be calculated, so depreciation cannot be estimated. From an accounting viewpoint this is a difficulty, but in production, the level of capacity utilisation is too variable, so unless this is known it is usually true that running costs have more explanatory power. These are reported and are aggregated to give an input of total running **costs of milking machinery**, buildings and equipment. The items included are electricity, repairs and maintenance of fixed improvements (such as milking sheds), sundry costs, insurance and other miscellaneous costs. The other capital item is for **other machinery running costs** and it is comprised of the costs of fuel, lubricants, tractor repairs and maintenance, implements repair and maintenance, and other miscellaneous running costs.

There are several variables that may also play a part in explaining efficiency differences amongst dairy farms, but initially only the most obvious were included, which is the percentage of the herd that is not producing milk. This varies over time, as it is never possible to keep a herd where all the animals produce all the time.

4.5 Preliminary data analysis

The variables above are summarised in Table 6, which reports the maximum, mean and minimum values of the variables for the sample and their standard deviations for all the years, using the current price data. Although there is plenty of variation to allow estimation, the differences are not enormous. The largest farm is less than six times the area of the smallest, a pattern that is reflected in the other variables. As they are similar commercial farms in the same area, this is to be expected. The standard deviation indicates a high degree of heterogeneity among production decisions of farms in the same group. The figures show that all the variables under consideration show significant variation both within and between farms, a finding that justifies the use of panel data techniques, in particular the fixed-effects estimator that relies on 'within' variation. Although one might expect the farms in the same area to be somewhat homogenous, it is important to highlight that there are differences that are not completely captured by the data set. For example, land as measured in hectares does not take into account differences in soil fertility or slope. Similarly, feed for dairy cows is an aggregate measure of different types of feed, which may vary in quality as well as composition. Furthermore, a measure of the managerial skills of the farmer is not included. All these factors lead to intrinsic heterogeneity that needs to be captured by panel data techniques, as has been observed in recent literature (i.e. Abdulai & Tietje, 2007; Farsi, Filippini & Kuenzle, 2005).

The same effect is perhaps even more clearly shown by Figure 16, which is a histogram of all 293 output observations. It suggests that the distribution of the dependent variable is approximately normal, with less dispersion around the mean than the standard normal distribution. The one minimum of zero was for percent cows not in milk for one farm in one year, which is possible, if unlikely that every single cow was producing milk on that farm in that year.

Table 6: Summary statistics for the production function variables

	Maximum	Mean	Minimum	Std. Dev.
Output – (R)	819 182	266 529	46 943	138658
Land - Hectares	455	205	84	76
Labour – number of workers	52	21	10	7
Labour – cost (R)	75 588	23 704	1 049	11 932
Feed – cost (R)	1 165 930	166 288	18 346	149 515
Veterinary – costs (R)	260 001	315 61	2 134	40 728
Tractors and equipment (R)	397 164	37 781	683	57 958
Milking machinery (R)	218 579	24 559	454	35 556
% Cows not in milk	44	18	0	8

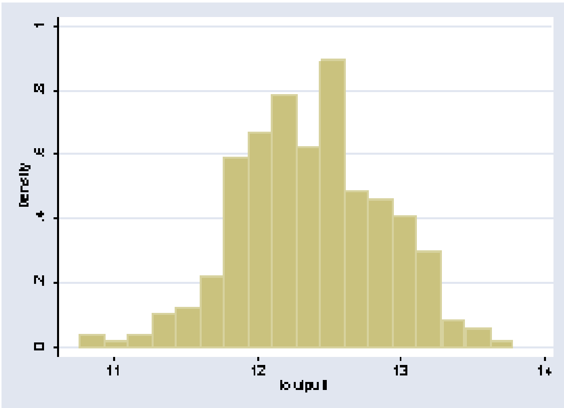


Figure 11: Histogram of log of output

Table 7 completes this preliminary analysis by reporting the correlation coefficients between the variables. These appear to be well behaved, with all the inputs being strongly positively correlated with output, as they should be for a production relationship. The weakest is the number of farm workers, which is much less correlated with output than is labour cost. This suggests that there are substantial variations in labour quality that are reflected in output. The single variable that is negatively correlated with output and all the other variables is the percentage of the herd not in milk, which is also to be expected.

Table 7: Correlation coefficients for production function variables in current prices

	Output	Land	Labour	Labour cost	Feed cost	Vet costs	Tractors Etc.	Milking machinery	% cows not in milk
Output – (R)	1								
Land - hectares	0.5402	1							
Labour - numbers	0.2747	0.5066	1						
Labour – cost (R)	0.6818	0.5329	0.5107	1					
Feed – cost (R)	0.5954	0.429	0.3124	0.5165	1				
Veterinary – costs (R)	0.6552	0.5311	0.2792	0.4608	0.6159	1			
Tractors etc. –cost (R)	0.5898	0.4676	0.2722	0.4348	0.5539	0.7328	1		
Milking machinery (R)	0.6596	0.4097	0.1869	0.4216	0.5147	0.6781	0.6663	1	
% cows not in milk	-0.1847	-0.0529	-0.0214	-0.0797	-0.0835	-0.2237	-0.1216	-0.1376	1

4.6 Deflators and constant 2001 price data

It is always possible to pool several years of data to increase the sample size and thereby increase the number of significant variables, but this raises complications. There are statistical tests to determine if pooling is a valid approach and these will be undertaken in due course. But, before pooling data with a time dimension, the variables have to be made inter-temporally comparable by deflating the current values to give constant price variables. This needs to be done for all the variables expressed in value terms, in order that the changes in the physical quantities of outputs and inputs, which is what the production function models, can be separated from changes in prices.[6] The current price data from Tammac Consultants does not include appropriate deflators, so each variable must be deflated by the most suitable deflator available. The source of deflators is the Abstract of Annual Statistics (AAS) (DAFF, 2007) and even when a variable such as fertiliser can be deflated with the fertiliser price index from the AAS, the process is a new source of errors. This is inevitable as the national prices may not be the same as the local prices in Midlands and because the deflator is for a fertiliser mix which is probably different from that used by dairy farmers. With aggregates for items like farm machinery, this problem is obviously more serious and for some items there really is no appropriate deflator available.

[6] Suppose that all the outputs and inputs are measured in value terms. If inflation affected all at exactly the same rate, deflation would not be necessary as the relationship between inputs and outputs would be unchanged. But suppose that all the prices and hence values stayed the same from year t to year t+1, except that the government doubled the wage by administrative fiat. Supposing too that the farms could not employ less labour, the labour cost input would double and production would appear to have decreased in efficiency as twice as much labour is needed. Obviously, the wage bill needs to be deflated by a wage index that has doubled, in order that the true unchanged production relationship can be identified.

Deflation is a necessary evil in the generation of variables that are the equivalent of physical quantities and these are the requirement for fitting production functions. Note too, that the intention is to model the production process from the viewpoint of the decision-makers, who in this case are the farmers.

4.6.1 Deflating output

The outputs were discussed in Section 4.4, which listed the three outputs reported in the data. Fresh milk is the most important output (called product income) and this include both the litres of milk produced and the value, so value divided by quantity gives prices. These vary by farm (due to quality differences) and over time. With this much information there are three alternative ways to create the constant price series. 2001 was chosen as the base year for prices, partly because it is the first year for which the full sample of 37 is available.

Table 8 shows the correlations between the three alternatives, which do vary considerably. The average price of milk in 2001 was R1.40[7], so if there is doubt as to the validity of the price differences between farms, all the constant values can be calculated by multiplying the litres of output by this fixed price (Milk 1 in Table 8). For simple functions like the Cobb-Douglas, a multiplicative constant simply ends up in the intercept term, so this is equivalent to using quantities, with no quality adjustment.

Alternatively, the quantities for each farm in each year can be multiplied by that farm's 2001 price, which imposes constant prices while allowing for quality differences (Milk 2 in Table 8). However, this assumes that the 2001 quality differences remained the same from 1999 to 2007, which seems unlikely.

Finally, the values for each farm for each year can be deflated by the fresh milk price index from the AAS, which allows for quality differences that change over time, but introduces distortions, as explained earlier (Milk 3 in Table 8).

Table 8: Alternative constant milk outputs

	Milk1	Milk2	Milk3
Milk 1 2001 average price	1.0000		
Milk2 2001 farm prices	0.9366	1	
Milk3 using national deflator	0.7989	0.8809	1

The choice between the three alternatives is an empirical judgement. 2) is preferred to 1) if the inter-farm price differences are correct, which they thought to be, but 2) and 3) impart different errors. Although 3) is the normal solution as 2) is often not an option, 3) is only preferable if the national deflator is reasonably correct for milk prices in Midlands.

[7] Exchange rate: R7.55 to 1US$ and R10.89 to the UK£ (as of 18 May, 2010).

4.6.2: Deflating inputs

Of the inputs, only land is in physical quantities (hectares) and this is because there is no price to create a value to use as a share weight. All the other inputs are expressed as values and the quantities are unknown, so prices cannot be determined, except for labour. This is given as a quantity and a value, just like milk, so the same options are possible. Labour is numbers of workers, Labourcost01 is deflated using the 2001 wages throughout and Labourcost def is the values deflated by the consumer price index (CPI), as there is no consistent data on agricultural wages. Table 9 shows that the correlation between the basic numbers, the wage costs at 2001 wages and the wage costs deflated with the CPI index are quite low. These are certainly different variables and some experimentation is called for in estimation. The lack of a wage index exacerbates the problem and the CPI deflates less than any of the agricultural price indices, whereas the minimum wage legislation may well have pushed wages up faster than the CPI.

Table 9: Alternative constant labour inputs

	Labour	Labourcost01	Labourcost def
Labour	1		
Labourcost01	0.5874	1	
Labourcost def	0.5643	0.7141	1

The next variable is total feed, which is made up of purchased feed, deflated by the feed price index[8]; fertiliser, deflated by the fertiliser price index; seed, for which there is no close price index (but it is only a small share), was also deflated with the feed price index; pesticide, deflated with the price index for dips and sprays; and finally, other costs, including transport, deflated with the fuel price index, as this is a major determinant of transport costs. Total veterinary costs were deflated with the CPI as there is no well suited deflator in the AAS.

For the capital items, total running **costs of milking machinery**, buildings and equipment is made up of electricity, deflated with the fuel prices, repairs and maintenance of fixed improvements, deflated with the materials for fixed improvements index, sundry costs, insurance and other miscellaneous costs, deflated with the maintenance and repairs price index. The other capital item is **other machinery running costs,** comprised of the costs of fuel and lubricants, deflated with the fuel index; tractor repairs and maintenance, deflated with the repairs and maintenance price index; and other miscellaneous running costs, also deflated with the repairs and maintenance price index.

[8] The indexes in this and the ensuing paragraphs are taken from DAFF, 2009

Other variables are used, for instance in explaining the inefficiency estimates. Some, such as the percentage of the herd that are not in milk, do not need deflating. Others, such as gross capital investment do require deflating; in this case by the combined price index for machinery, trucks and implements as this really is a capital investment series.

The modelling of dairy farms is complex due to the multiple-inputs, multiple-output nature of production. Furthermore, some of the outputs produced are used in the production of other outputs thus rendering them as intermediate outputs. All the inputs used and outputs generated need to be accounted for in order to properly represent and describe the dairy production system. The proper modelling of the dairy industry is important because without such it would be difficult to estimate any meaningful production function of the system. The current chapter provides a thorough discussion of the data available for modelling of the efficiency of dairy farms. The alternative empirical approaches to production function estimation of the dairy farms in the KwaZulu-Natal Midlands are presented in the next chapter (Chapter 5).

Chapter 5: Alternative approaches to production function estimation

Panel data immediately confronts the researcher with choices which may be difficult. The correct level at which to estimate is seldom obvious. In this case, the first alternative, of estimating the time series separately, for each individual farm, is precluded by the lack of observations. With only nine data points, there are insufficient degrees of freedom to follow this option, although farms could be grouped according to size, to give several samples of sufficient size. This option becomes attractive if farm size is an issue and this will become apparent as results are generated. The other disaggregated alternative, of estimating the cross sections for individual years is viable, although the samples are perhaps too small to expect good results. This approach, using the current price data, is investigated first, before progressing to pooling the years or running the model as a panel. The different possible combinations of outputs and inputs (such as the three ways of calculating milk output) are all tried. The herd size is included to test if cows should be used as an input. Then, experimentation shows that some variables have more explanatory power when they are lagged one year. The first issue tackled is then choice of the functional form for the production function, which is done by testing the adequacy of the restrictive Cobb-Douglas against a flexible functional form. Then, for the panels, the preferred random effects model has to be tested against for consistency against the more restrictive fixed effects model.

5.1 Mean response functions for individual years using current value data

The preliminary data analysis in Chapter 4 suggests that these production data are likely to give sensible results, but the small size of the individual cross sections may well be a limitation, which cannot be corrected, as further data is not available. The data for these cross section regressions is not deflated as no inter-temporal comparisons are involved. The variables are assumed to be linear in logarithms, so the coefficients can be interpreted as elasticities. This simple Cobb-Douglas production function is chosen as alternatives such as the translog exhaust the degrees of freedom entirely. A six input Cobb-Douglas, with the dependent variable and a constant, leaves only 17 degrees of freedom, so the net approach is used here and the herd size is not included. The translog adds a further 15 squared and cross product terms and is clearly untenable. The small sample size of 25 is still reflected in the first set of results for 1999. Table 10 reports the results when only the three dominant explanatory variables are used. Production theory limits the range of the output elasticities to be between zero and unity, so the t-tests may be taken to be one tailed. With these small samples the confidence levels are as shown in the tables.

Thus, the t-statistic on the coefficient for land is just sufficient to be on the border of the 10% significance level. The elasticity of 0.27 means that a 1% increase in land will increase output by 0.27%, on average. Labour and feed are also significantly different from zero at the 10% significance level and the coefficients can be interpreted in the same way. The F statistic shows that variables jointly have explanatory power and the adjusted R^2 shows that land, labour and feed alone explain over half the variance in output. However, the three output elasticities sum to only 0.72, which implies either seriously decreasing returns to scale or misspecification, and indeed several explanatory variables have been omitted. This follows since increasing all inputs by 1% will increase output by only 0.72%.

Table 10: Results for 1999 with dominant variables only

Inputs	Coefficient	Standard Error	t	P>|t|
Ln land	0.269003	0.205916	1.31	0.103
Ln labourcost	0.178682	0.117287	1.52	0.072
Ln totalfeed	0.277185	0.16162	1.72	0.051
Constant	5.602145	1.36877	4.09	0.001
Number of observations = 25		F(3, 21) = 10.2		Adjusted R-squared = 0.5349
Dependent variable is Ln Output		Probability > F = 0.0002		Root MSE = 0.262

Including the omitted inputs does not solve the problem as Table 11 shows. Adding the other three explanatory variables results in a model for which all the test statistics are poorer and only feed is significant at the 10% confidence level. This is fairly typical of the results for the individual years, which are only pursued further to determine if any obvious patterns or changes over time can be identified.

Table 11: Results for 1999 with all inputs

Inputs	Elasticities	Standard Error	t	P>|t|
lland	0.229037	0.249409	0.92	0.181
lLabour cost	0.17188	0.136515	1.26	0.112
ltotal feed	0.281162	0.17334	1.62	0.62
ltotal veterinary	0.039279	0.104485	0.38	0.361
lOther machinery	-0.07057	0.144802	-0.49	0.312
lMilking machinery	0.052364	0.089728	0.58	0.287
constant	5.648963	1.484429	3.81	0.001
Number of obs = 25	F(6, 18) = 4.68	Adjusted R-squared = 0.4791		
Dependent variable is Ln Output	Probability > F = 0.0049	Root MSE = 0.27727		

l = the natural logarithm of the variables

The main results for all the individual years are reported in Table 12, which shows that the results are as good as can be expected for small cross sectional samples. The F statistics indicate that in all cases the variables collectively have explanatory power at the highest confidence levels and the average R^2 is 0.63. It would be unusual to explain more than two thirds of the variance with production data of this sort. However, in all cases the small samples mean that not all the variables are positive and significant. From 2000 to 2005, three of the six are significant and two in the last two years. The significant variables vary, but feed is significant only in the first two years. However, land, which is a large component of farm produced feed, is significant in four cases, so one of the feed-related variables is significant in two thirds of the regressions. The same is true of veterinary costs, while labour and the running costs of milking machinery are significant in five of the nine cases. The weakest variable is the running costs of other machinery, which is significant in only one year.

Table 12: Results for individual year with all inputs using current price data

Years	1999	2000	2001	2002	2003	2004	2005	2006	2007
Variables	**Elasticity**	**Elasticity**	**Elasticity**	**Elasticity**	**Elasticity**	**Elasticity**	**Elasticity**	**Elasticity**	**Elasticity**
land	0.229	0.020	-0.021	0.102	0.508	0.432	0.190	0.206	0.712
t-stat	0.92	0.12	-0.10	0.63	3.60**	2.38**	1.30*	1.13*	2.26**
llabourcost	0.172	-0.164	0.471	0.304	0.059	0.228	0.442	0.329	0.050
t-stat	1.26*	-0.95	2.96**	3.16**	0.46	1.33*	3.07**	1.72*	0.23
ltotalfeed	0.281	0.374	-0.067	-0.075	-0.070	-0.026	-0.153	-0.040	0.101
t-stat	1.62*	2.91**	-0.61	-0.93	-0.90	-0.26	-1.62	-0.40	1.31*
ltotalveterinary	0.039	0.367	0.153	-0.027	0.129	0.182	0.355	0.235	-0.42
t-stat	0.38	4.20**	1.53*	-0.29	1.52*	1.94*	3.64**	2.38*	-0.31
othermachinery	-0.071	-0.288	0.043	0.082	0.028	-0.036	-0.116	0.039	-0.075
t-stat	-0.49	-2.30	0.40	1.33	0.39	-0.33	-1.55	0.38	-0.64
milkingmachinery	0.052	0.141	0.169	0.179	0.091	0.079	0.029	-0.001	0.269
t-stat	0.58	2.49	2.28	2.44	1.78	1.13	0.44	-0.01	2.33
constant	5.649	7.236	4.940	7.441	7.612	6.089	6.210	5.889	5.837
t-stat	3.81**	5.62**	3.46**	6.78**	7.68**	4.84**	5.16**	3.88**	3.083**
Number of obs	25	25	37	37	37	37	37	36	22
F(6, dof)	4.58	12.13	8.12	7.73	15.21	11.7	13.54	9.38	10.81
Prob > F	0.005	0.000	0.00	0.00	0.00	0.00	0.00	0.00	0.0001
Adj R-squared	0.479	0.736	0.543	0.529	0.703	0.641	0.676	0.590	0.737
Root MSE	0.277	0.199	0.324	0.266	0.210	0.246	0.245	0.280	0.252

** Significant at 5%. * Significant at 10%

5.2 Mean response functions for individual years using constant price data

To improve on these results it is necessary to pool the years and as the data chapter explained, this requires that the variables all be deflated, to allow comparisons over time. The deflators were explained in Chapter 4 and there are substantial differences between the current and constant price data. This is apparent if the correlation coefficients for the current price data, reported in Table 12 are compared with those for the constant 2001 price data in Table 13.

Table 13: Correlation coefficients for production function variables at constant prices

	loutput	**lland**	**llabour**	**llabourcost**	**ltotfeed**	**ltotvet**	**Lrcmilk mac**	**Lrcoth mach**	**drycows**
loutput	1								
lland	0.5566	1							
llabour	0.2858	0.5066	1						
llabourcost	0.5132	0.5732	0.5643	1					
ltotalfeed	0.3442	0.3758	0.2617	0.3094	1				
ltotalvet	0.4745	0.4214	0.1711	0.3028	0.5159	1			
lmilkingmac	0.4955	0.4081	0.1904	0.3345	0.3681	0.5191	1		
lothermac	0.4613	0.4723	0.2841	0.3497	0.4475	0.5442	0.6214	1	
drycows	-0.1988	-0.0529	-0.0214	-0.0295	-0.0508	-0.1393	-0.1343	-0.1234	1

Although some of the correlations are increased slightly, such as those between output, land, labour numbers and cows not in milk, the rest of the correlations between income and the inputs are quite seriously diminished. This may be because the price inflation element increased the previous correlations above the levels that would have prevailed with just quantity changes, or because the inaccuracy of the inappropriate deflators has now partially destroyed the true correlation. Most likely, both causes are present, but the outcome is clearly lower average correlation between output and incomes, which may well mean the production function will fit less well.

This possibility can be tested by repeating the annual OLS regressions using the constant price data. The results of this exercise are reported in Table 14, which shows that although there is some grounds for the pessimism above, the deflation process does not damage the production relations greatly. The average R^2 is reduced from 0.63 to 0.55 and instead of 23 significant coefficients with the correct sign, there are now only 19. However, there is now less variability, with all the models having an R^2 above 0.5 and all having at least two significant positive elasticities. The basic problem of small samples and insignificant variables remains unchanged, so the next step is to investigate pooling the annual data.

Table 14: Results for individual year with all inputs using constant 2001 price data

Years	1999	2000	2001	2002	2003	2004	2005	2006	2007
Variables	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity	Elasticity
land	0.344	0.131	-0.033	0.026	0.435	0.433	0.093	0.231	0.840
t-statistic	1.46	0.60	-0.17	0.15	2.37**	2.01**	0.50	1.19	2.02**
llabourcost	0.228	0.087	0.472	0.396	0.092	0.022	0.484	0.342	0.057
t-statistic	1.17	0.38	3.02	3.98	0.55	1.07	2.67	1.68	0.20
ltotalfeed	0.134	0.200	-0.068	-0.100	-0.154	-0.036	-0.136	0.013	0.037
t-statistic	1.18	1.18	-0.62	-1.21	-1.52	-0.30	-1.13	0.12	0.36
ltotalvet	-0.187	0.239	0.144	0.046	0.178	0.010	0.390	0.212	0.028
t-statistic	-2.39	2.08	1.51	0.54	1.64	1.57	3.12	2.201	0.16
milkingmac	0.038	0.154	0.165	0.162	0.049	0.087	-0.011	-0.023	0.262
t-statistic	0.40	2.07	2.26	2.14	0.71	1.06	-0.13	-0.28	1.58
othermac	0.215	-0.269	0.071	0.041	0.103	0.147	-0.090	.035	-0.029
t-statistic	1.67	-1.62	0.73	0.65	1.06	1.17	-0.95	0.32	-0.19
constant	6.142	7.352	4.879	6.855	7.223	4.710	5.446	5.030	4.184
t-statistic	2.78	4.29	3.45	5.69	5.64	3.04	3.70	3.20	2.15
Number of observation	25	25	37	37	37	37	37	36	22
F(6, dof)	5.42	5.12	8.29	8.19	10.07	8.16	8.30	8.05	6.32
Probability > F	0.0023	0.0032	0.000	0.000	0.00	0.00	0.00	0.00	0.0018
Adjusted R-squared	0.525	0.507	0.548	0.545	0.602	0.544	0.549	0.547	0.603
Root MSE	0.270	0.264	0.322	0.273	0.272	0.301	0.309	0.299	0.324
** Significant at 5%. * Significant at 10%.									

5.3 Pooling cross section and time series

There are no problems preventing joint estimation of the nine years of data and Baltagi (2005) notes that whilst testing to determine if different entities, such as farms, should be pooled, testing is not normally applied to years. Thus, at this juncture, the nine years of data are simply pooled and the OLS mean response functions estimated, with a sample of 293 observations. Pooling amounts to a form of aggregation, which will hopefully produce more robust estimates, but at the cost of destroying information, in the sense that there will be only one set of elasticity estimates for all nine years.

Only three of many sets of results are shown, as these are sufficient to explain the range of results. The dependent variable in Table 15 is total income using the milk price deflator (Milk 3) for the product income component, as explained in Chapter 4. With the full sample of 293 observations, the F statistic is far larger, but the R^2 is actually lower than it was for the annual samples, which is reasonable, as there are now time series variations to explain as well as cross sectional differences, which also give a slight increase in the mean squared error (MSE). However, the huge increase in degrees of freedom causes substantial increases in the significance level of the inputs. Land has the largest elasticity, with a one percent increase changing output by 0.25%. Labour comes second in terms of impact (the constant 2001 prices were used rather than the series that was deflated by the CPI). Next is feed, but notice that purchased feed is the variable used. In the annual results using the constant price data, total feed was never significant and this was also true with the pooled sample. This means the deflated series for fertiliser, seed and plant protection chemicals no longer contributes to the explanatory power of the feed variable and indeed makes it ineffective. Land is the dominant input for farm produced feed and it may be that farms that grow good pasture with low or no inputs of chemicals and seed produce as well as those that need such inputs. Thus, land is the best input to represent farm produced feed and the feed variable can be reasonably reduced to just purchased feed.[9]

Table 15: Pooled sample results with income from milk deflated by the AAS milk price

				Number of observation = 293
				F(7, 285) = 40.58
				Probability > F = 0.0000
				R-squared = 0.4992
				Adjusted R-squared = 0.4869
				Root MSE = .3226
Dependent variable = output				
loutput	Coefficient	Standard Error	t	Probability>|t|
lland	0.248463**	0.073968	3.36	0.001
Llabourcost01	0.183208**	0.053814	3.4	0.001
lpurchasedfeed	0.15**	0.033488	4.48	0
ltotalveterinary	0.068263	0.025165	2.71	0.004
lmilkingmachinery	0.092516	0.02696	3.43	0.001
lothermachinery	0.03473	0.032371	1.07	0.142
SUM	0.77			
drycows	-0.00639	0.002595	-2.46	0.007
_constant	5.589966	0.495805	11.27	0
**Significant at the 5% level				

The next input in terms of impact is milking machinery, with an elasticity of 0.09, followed by veterinary expenses, at 0.06. Unlike the yearly results, all these five inputs are significantly different from zero at the highest confidence levels.[10] The only exception is other machinery, which has a smaller elasticity and is not significant. Perhaps it is not surprising that this variable is less closely connected with output. It includes repairs and maintenance, which actually had a negative impact on output that could mean that older tractors on farms that are doing less well break down more often.

[9] There is a case here for reporting this negative impact of seeds and chemicals to Tammac, who may have an explanation or may be interested to be informed so they can investigate.

[10] With over 200 degrees of freedom the critical value for a one tailed test at the 10% confidence level is 1.28, for 5%, the figure is 1.65 and 2.33 is sufficient for 0.5% confidence. A one tailed test is appropriate for the elasticities if the values are constrained by theory to be between zero and unity.

However, even fuel and lubricants had a negative impact, which is harder to rationalise. One possible explanation could be that old tractors are less fuel-efficient and require frequent servicing which, in turn, uses more lubricants. In all, it is best to simply note that this variable has less explanatory power, as the next models will show it often is significant.

The last variable is the percentage of the herd that is not in milk. This is not an input, but a fairly obvious adjustment to make the regression more accurate, since inputs are still needed to tend unproductive cows. A dairy herd will almost always have a proportion of unproductive animals, particularly young animals, so it is no surprise that this variable is negative and highly significant, despite the small impact of only -0.006. Last, the sum of the output elasticities can be taken to indicate the scale efficiency of the farms. In this case the sum of the output elasticities is only 0.78, even if the insignificant effect of other machinery is included. If this result were true, it would mean that increasing the size of the farms by 1% would increase output by only 0.78%, which implies that the average farm in this sample is in the range where decreasing returns to scale has set in. Quite simply, the farms are too big and output would be increased by having more and smaller farms. However, this simple calculation is not reliable. The apparent decreasing returns could be caused by misspecification: if inputs have been omitted this would be the case. It is also only an average: if half the farms were too big and half too small, the average could show constant returns to scale, meaning that the farms are the right size, when in fact none of them are. For these reasons, returns to scale is ignored here and returned to once the models are better specified and the estimation techniques have been refined.

The suggestion above that the dominant cause of having a higher proportion of cows not in milk is attributable to expanding the herd and having a lot of young animals is substantiated by adding the same variable, but with a two period lag (Table 16). This lagged variable is positive and significant, which can be interpreted as meaning that after two years the young animals are contributing and the farm that was disadvantaged by having a high proportion of young animals now does better than farms that were not in this position. Adding the lagged variable requires care in a panel dataset to maintain the coherence of the individual farms[11]. This procedure reduces the sample size to 210 and this lowers the F statistic but note too that the R^2 is substantially improved.

[11] In Stata this requires setting the tsset farmid year, yearly command. Then we construct the lags using: bysort farmid (year): gen drycow2 =drycow[_n-2].

Table 16: Pooled sample results with lagged cows not in milk

	loutput
lland	0.324
	(4.33)***
llabourcost	0.211
	(3.56)***
lpurchasedfeed	0.125
	(3.42)***
ltotalveterinary	0.035
	(1.14)
lmilkingmachinery	0.083
	(2.69)***
lothermachinery	0.071
	(2.06)**
Drycow lagged 2 years	0.005
	(1.66)*
drycows	-0.006
	(2.16)**
Constant	5.065
	(9.70)***
Observations	219
Adjusted R-squared 0.55	F (8, 210) = 34.54
Absolute value of t-statistics in parentheses	
* significant at 10% level; ** significant at 5% level; ***significant at the 1% level.	

In this model the variable that is now insignificant is veterinary expenditures. These are the costs of medicines and veterinary visits, the costs of artificial insemination (AI) and semen and other expenses. The AI and semen is a basic requirement and should correlate well with output, but as the correlations in Table 17 show, the correlation with output is quite low. It may well be that the gestation period is sufficiently long that the AI and semen costs should be lagged one year and the same may be true of other costs. Medicines and veterinary visits may also be at a time when output is reduced by say disease and have a positive payoff in the next period. These suggestions are perhaps speculation as to why, but there is no doubting the results. If the total veterinary costs are lagged one year the elasticity is three times larger and highly significant, as Table 18 shows. In this model, using lags has made all the input elasticities significantly different from zero and the explanatory power has increased, as the model now explains 58% of the variance in the output/income variable.

Table 17: Correlation coefficients for income and veterinary costs

	loutput	ltotalvet	lmedicine	lai	lothervet
loutput	1.0000	0.4745	0.4747	0.1884	0.3073
ltotalvet		1.0000	0.6109	0.2798	0.3746
lmedicine			1.0000	0.2055	0.4511
lai				1.0000	0.2091
lothervet					1.0000

ai=artificial insemination

Table 18: Results with lagged veterinary costs

Dependent variable = output	
lland	0.300
	(4.17)**
llabourcost	0.190
	(3.30)**
lpurchasedfeed	0.110
	(3.11)**
ltotalveterinary^{-1}	0.102
	(3.86)**
lmilkingmachinery	0.066
	(2.25)**
lothermachinery	0.058
	(1.76)*
drycow^{2}	0.004
	(1.54)*
drycows	-0.006
	(2.08)**
Constant	5.212
	(10.28)**
Observations	219
Adjusted R-squared	0.58
Absolute value of t statistics in parentheses	
* significant at 5%; ** significant at 1%	

The next model, reported in Table 19, uses an output variable in which the milk price is held constant by using the 2001 prices. The appropriate comparison is with the Table 15 results, so there are modest improvements in all four test statistics, which suggests that the milk deflator may cause more damage to the underlying constant price relationship between outputs and inputs than diminishing the quality variation over time. There are minor changes in the elasticities, with those for land, feed and both machinery variables increasing, while those for labour and veterinary costs fall. Despite these changes, the relationships appear to be stable and the sum of the elasticities also increases slightly to 0.81. The most important change is that all the elasticities are significantly different from zero and all but veterinary costs (significant at the 10% level) are significant at high levels of confidence.

Table 19: Pooled sample results with income from milk at the 2001 milk price

	Number of observations = 293			
	F(6, 286) = 58.02			
	Probability > F = 0.0000			
	R-squared = 0.5490			
	Adjusted R-squared = 0.5395			
	Root MSE = .30226			
loutput	Coefficient	Standard Error	t	Probability>|t|
lland	0.273628**	0.069298	3.95	0
llabourcost	0.139858**	0.050268	2.78	0.003
lpurchasedfeed	0.185275**	0.031081	5.96	0
ltotalveterinary	0.032768	0.023536	1.39	0.086
lmilkingmachinery	0.12159*	0.025241	4.82	0
lothermachinery	0.059427	0.030312	1.96	0.026
sum	0.81			
constant	5.354088	0.457605	11.7	0
* significant at 5%; ** significant at 1%				

The final model (Table 20) uses milk in litres valued at the average 2001 price, in order to give a reasonably correct weight relative to trading income and other income. As it was argued in Chapter 4, this is equivalent to treating milk output as litres with no quality adjustment. The results, in Table 20, show this cruder measure leads to considerable improvements in the entire test statistics (relative to Table 15), with almost two thirds of the variance now explained instead of less than half in the first regression. The other change is that the labour variable used here was deflated with the CPI and this does increase the output elasticity of labour to over 0.2, perhaps because it does take full account of labour quality differences. The other elasticities are relatively stable and all the variables are significant, although veterinary costs is borderline and other machinery is also relatively weak. The weak effect of other machinery was discussed above and the relatively weak effect of veterinary costs is also quite possibly real rather than being just a result of poor data. Some of the components like AI and semen could be described as proactive and are closely related to output, but the costs of medicines and vet's visits are reactive, in that they are usually a response to problems and hence can be inversely related to output. Finally, the elasticities sum to 0.82, so the simple argument on returns to scale still says the farms are too big. These results are used in deciding which variables to include in the more complex models that follow.

Table 20: Pooled sample results with milk in litres

					Number of observations = 293
					F(6, 286) = 84.29
					Probability > F = 0.0000
					R-squared = 0.6388
					Adjusted R-squared = 0.6312
					Root MSE = .25297
loutput	Coefficient	Standard Error	t	P>|t|	[95% Conf. Interval]
lland	0.259072**	0.054241	4.78	0	.1523098 .3658348
llabourcost	0.224181**	0.043874	5.11	0	.1378238 .3105372
lpurchasedfeed	0.145124*	0.026899	5.4	0	.0921786 .1980702
ltotalveterinary	0.025013	0.019692	1.27	0.103	-.0137455 .0637716
lmilkingmachinery	0.133612*	0.021125	6.32	0	.0920327 .1751922
lothermachinery	0.034544	0.025384	1.36	0.087	-.015419 .0845067
sum	0.82				
constant	5.226774	0.364699	14.33	0	4.50894 5.944609
* significant at 5%; ** significant at 1%					

5.3 Developing a gross output and input approach

The pooled data models used so far follow the net outputs and inputs approach. If the gross basis is used, the most theoretically correct model would have separate equations for the gross output of farm feed, the production of the cows that comprise the dairy herd and finally the production of milk. This system of equations would follow the pattern below with three equations and six identities adding up constraints for the inputs. Unfortunately, the allocation of the inputs between activities is not known.

$$FPF_{t+1} = f\left(A_{ft}, L_{ft}, T_{ft}, F_{ft}, S_{ft}, C_{ft}, O_{ft}\right) \tag{5.1}$$

$$Cows_{t+1} = g\left(A_{ct}, L_{ct}, PF_{ct}, V_{ct}, FPF_{ct}, T_{ct}\right) \tag{5.2}$$

$$Milk_{t} = h\left(COWS_{mt}, A_{mt}, L_{mt}, V_{mt}, PF_{mt}, FPF_{mt}, MM_{mt}, T_{mt}\right) \tag{5.3}$$

$$A_{tt} = A_{ft} + A_{ct} + A_{mt} \tag{5.4}$$

$$L_{tt} = L_{ft} + L_{ct} + L_{mt} \tag{5.5}$$

$$T_{tt} = T_{ft} + T_{ct} + T_{mt} \tag{5.6}$$

$$V_{tt} = V_{ct} + V_{mt} \tag{5.7}$$

$$FPF_{tt} = FPF_{ct} + FPF_{mt} \tag{5.8}$$

$$L_{tt} = PF_{ct} + PF_{mt} \tag{5.9}$$

In the first equation, the gross output of farm produced feed (FPF) is a function of land and labour used for farm feed, and the inputs of fertiliser (F), seed (S), pesticides and herbicides (C), and other costs including transportation (O). Note that in the estimations so far only purchased feed has been included as the net basis was used. For the gross basis, we would need the output of FPF, which is not reported at all, so to estimate (5.1) would require a programme such as Lisrel, which handles unobservable variables. In fact, land and labour have already been included and the proportion going to FPF production is not known. This leaves fertiliser, seed, chemicals and other costs, which have not so far been included in the list of inputs. In later estimates, the value of these inputs are summed and used as a proxy for the input of FPF, but it is really not practical to even attempt estimation of (5.1).

Table 21: Seemingly unrelated regression with variable "cows in milk" (2001 base year)

Equation	Observation	Parms	RMSE	R-squared	Chi-quared	P
(1) loutputmd	256	8	.2547744	0.6566	487.16	0.0000
(2) lcownumber	256	4	.1202996	0.8428	1372.76	0.0000
Loutputmd	Coefficient	Standard Error	z	P>|z|	[95% Conf. Interval]	
llandmd	0.1590789**	0.0597225	2.66	0.008	0.0420249	0.2761328
llabourmd	0.1654852**	0.051995	3.18	0.001	0.0635768	0.2673936
lfeedmd	0.0559763	0.030338	1.85	0.065	-0.003485	0.1154377
lvetmd1	0.0527947	0.020336	2.60	0.009	0.0129368	0.0926526
lmilkmamd	0.1049431*	0.0208638	5.03	0.000	0.0640507	0.1458354
lothermacmd1	0.0645667	0.0265819	2.43	0.015	0.012467	0.1166663
lcownumber	0.4100623	0.0745551	5.50	0.000	0.263937	0.5561875
ldrycows	-0.0065821	0.0021991	-2.99	0.003	-0.0108922	-0.0022719
_cons	-2.089347	0.4044908	-5.17	0.000	-2.882134	-1.29656
Dependent variable: Number of Cows (lcownumber)						
lcows in milk	0.5503122**	0.02228	24.70	0.000	0.5066442	0.5939802
llabourmd	0.0735242	.0238271	3.09	0.002	0.0268239	0.1202244
lfeedmd	0.0374847	.0136698	2.74	0.006	0.0106923	0.0642771
llandmd	0.0637729	.0256116	2.49	0.013	0.0135751	0.1139708
constant	2.573071	.1161412	22.15	0.000	2.345438	2.800703
md= data mean differenced; **significant at the 5% level; *significant at the 10%						

For equation (5.2), the number of cows in the herd is observable and all the inputs can be measured although the proportion allocated to cow production rather than to farm produced feed or milk is not observable. Even so, it is quite possible to estimate this equation in combination with equation (5.3), which models milk output as a function of the six original inputs and the herds of dairy cows. Notice that farm produced feed and herd size both appear as outputs and inputs hence the sense in which they can be cancelled out in the net approach.

The last two equations are estimated as a system using seemingly unrelated regression (SUR).

The output equation explains two thirds of the variance, which is a little better than in the previous models. The biggest difference is in the sum of the output elasticities, which was no higher than 0.82 in the net approach, but now sum to 1.01. This is not significantly different from unity, which would suggest constant returns to scale (CRTS). This would be in line with expectations, as the farms are really similar and there is no real reason to expect substantial returns to scale.

In the herd production equation, land, labour and purchased feed are significant, but the explanatory power is in large part due to the inclusion of cows in milk. Obviously, the herd of animals at breeding age is a key variable in explaining the production of new animals, but including what is practically a lagged dependent variable increases the percentage of the variance explained from about 40% to 85%. This is shown in the next set of results in which the lagged dependent variable is used as presented in Table 22. The test statistics indicate that this model is almost as good and it again has the advantage of the elasticities adding to 0.95, which is very close to unity and hence would be consistent with CRTS.

Table 22: Seemingly unrelated regression with herd size (number of cows)

Equation	**Observation**	**Parms**	**RMSE**	**R-squared**	**Chi-squared**	**P**
loutput01md	256	8	0.2548	0.6565	492.89	0.0000
lcownumber	256	4	0.1219	0.8386	1330.28	0.0000
loutput01md	Coefficient	Standard Error	z	P>|z|	[95% Conf. Interval]	
llandmd	.1535459**	.0597215	2.57	0.010	.0364939	.2705979
llabourmd	.1538184**	.0519946	2.96	0.003	.0519108	.255726
lfeedmd	.0509805	.0303376	1.68	0.093	-.0084801	.1104411
lveterinarymd1	.0519233	.0203338	2.55	0.011	.0120698	.0917767
lmilkmacmd	.1053371**	.0208615	5.05	0.000	.0644493	.146225
lothermacmd1	.0640845	.026579	2.41	0.016	.0119905	.1161784
lcownumber	.4505058**	.0745515	6.04	0.000	.3043876	.5966241
ldrycows	-.0068188	.0021989	-3.10	0.002	-.0111285	-.0025092
constant	-2.305039	.4044753	-5.70	0.000	-3.097796	-1.512282
Dependent variable: Number of Cows (lcownum)						
lcownum1	.865635	.0357123	24.24	0.000	.7956401	.9356299
llabourmd	.0539713	.0244812	2.20	0.027	.005989	.1019535
llandmd	-.0074345	.0265316	-0.28	0.779	-.0594354	.0445665
lfeedmd	.02764	.0139599	1.98	0.048	.0002791	.0550009
constant	.7745684	.1924493	4.02	0.000	.3973748	1.151762
md= data mean differenced; 1=lagged one year; loutput01= output (2001 base year); **significant at the 5% level						

This multiple equation approach adds to our understanding and shows that it is possible to model the underlying gross output approach to estimation where the farm produced inputs appear as outputs as well. Whilst this line of enquiry is of some interest, the limitation is that the multiple equation approach precludes other developments, such as fitting panels and estimating frontier production functions.

Can this gross basis be simplified or improved? One alternative would be to add the two intermediate outputs of FPF and cows to the existing three outputs of milk, feed and animals. This is sticking to the gross output accounting concept, but again adds little to the model except more sources of error. The most pragmatic approach is in fact the one that is followed next. That is to simply include herd size in the single production function equation and drop the other two equations. Many models proceed in this manner without justification, so the investigation above could even be regarded as unduly pedantic, but it is possibly a fruitful line of enquiry to develop later.

5.4 Selection of an appropriate functional form

In the last section all the variables were linear in logarithms, which is a convenient and simple model, commonly known as the Cobb-Douglas (CD) production function. However, as was discussed in the theory in Chapter 2, the CD is a remarkably restrictive functional form. It assumes that all variables are linear in logarithms and that the elasticity of substitution between any pair of variables is always equal to unity. As these constraints are unlikely to be accepted in models fitted to an adequate number of observations, for these pooled models it is necessary to test that the CD is an adequate representation of these data. This test of adequacy is performed by comparing the constrained model (CD) with an unconstrained model in which it is nested. The unconstrained functional form most commonly used is the Translog (TL), which is a flexible functional form. This means that it can adequately represent many unknown underlying true production functions. To do this the function has to be more flexible than the CD, and this is achieved by adding a squared term for each variable to allow for non-linearities, and cross products of all the inputs, which allows for interaction between variables. Thus, the elasticities of substitution can be estimated rather than imposed and can be different for each pair of inputs.

Thus, the functional form of the stochastic frontier was determined by testing the adequacy of the CD relative to the less restrictive TL. The OLS models estimated are defined as

$$y_{it} = \beta_0 + \sum_{j=1}^{6} \beta_j x_{jit} + \varepsilon_{it} \qquad \textbf{(5.10)}$$

and

$$y_{it} = \beta_0 + \sum_{j=1}^{6} \beta_j x_{jit} + \sum_{j=1}^{6} \sum_{h=1}^{6} \beta_{jh} x_{jit} x_{hit} + \varepsilon_{it} \qquad \textbf{(5.11)}$$

respectively. The y is the log of output, and the six independent variables (x_j) are the logarithms of land, labour, purchased feed, veterinary costs, milking machinery and other machinery and implements. The i subscripts denote the farms and the t subscripts the year of observation.

The OLS estimates of the parameters in the CD and TL stochastic frontier production function models defined by (5.1) and (5.2) are reported in Table 23. If the TL is estimated for this production function with six inputs, it adds six squared terms and fifteen cross product terms to the original CD as equation 5.2 shows. Before estimation, the data is mean centred, which is a matter of calculating the mean of each variable across the 293 observations and subtracting this from the original series. This is necessary to avoid complex calculations to retrieve the elasticities and their standard errors. Using a two input production function for simplicity

$$\ln y = b_0 + b_1 \ln x_1 + b_2 \ln x_2 + \left(\tfrac{1}{2}\right)\left[b_{11}(\ln x_1)^2 + b_{22}(\ln x_2)^2\right] + b_{12} \ln x_1 \ln x_2 \qquad \textbf{(5.12)}$$

If in logarithms, we subtract from each column of input data its sample mean, we are simply changing the units of measurement of each variable. This is no different to changing a labour measure from weeks to hours by multiplying all values by 40. It has no material effect upon the results obtained. However, the advantage of subtracting the mean is that the mean of each logged variable is now equal to 0. When we calculate the partial derivatives, the output elasticity of x_1 is

$$\frac{\partial \ln y}{\partial \ln x_1} = b_1 + b_{11} \ln x_1 + b_{12} \ln x_2 \qquad \textbf{(5.13)}$$

Thus, the elasticity is data dependent and cannot be read off from the output, but has to be calculated as above. The trick is that it is normal to evaluate the elasticities at the sample means, so with the means of $\ln x_1$ and $\ln x_2$ equal to 0, the elasticity is simply equal to the first order coefficient, b_1. This is simply the direct (or CD) term.

The TL results, reported in the first column of Table 23, show that one squared term and five cross products are significant. This suggests that the TL will be an appropriate representation of these data, as it is unlikely that these six coefficients will be jointly insignificant in any statistical test. The direct (CD) terms are all significant at the 5% confidence level or better, except for other machinery, which is negative and insignificant. This is probably the result of collinearity of this relatively weak variable with some of the 21 additional variables. The elasticities still sum to only

0.833, so the possibility of decreasing returns to scale persists. This is of some interest since farm size has been increasing substantially for some time in the Midlands, due to the small margins on dairy production. This raises the possibility that the farms are actually too big already and that continued increases in farm size will lower efficiency rather than improve it. This aspect will be pursued further in due course.

Table 23: Translog results for pooled data compared with the Cobb-Douglas

Dependent variable: Output	(1) Translog	(2) CobbDouglas
	Output	OutputMD
LLANDMD	0.276 (3.76)**	0.277 (3.98)**
LLABOURMD	0.167 (2.51)*	0.185 (3.28)**
LFEEDMD	0.289 (5.93)**	0.142 (4.10)**
LVETERINARYMD	0.045 (1.72)*	0.070 (2.78)**
LMILKINGMACHINERYD	0.056 (1.85)*	0.085 (3.14)**
OTHERMACHINERYMD	-0.010 (0.24)	0.029 (0.90)
$LLANDMD^2$	-0.247 (1.13)	
$LLABOURMD^2$	0.096 (1.07)	
$LFEEDMD^2$	0.047 (2.51)*	
$LVETERINARYMD^2$	0.004 (0.17)	
$LMILKINGMACHINERYD^2$	-0.030 (1.17)	
$LOTHERMACHINERYMD^2$	-0.018 (0.57)	
LANDLABOUR	0.028 (0.12)	
LANDFEED	-0.213 (1.26)	
LANDVETERINARY	-0.175 (1.94)*	
LANDMILKMACHINERY	0.096 (0.87)	
LANDOTHERMACHINERY	0.249 (2.10)*	
LABOURFEED	0.095 (0.76)	
LABOURVETERINARY	-0.174 (2.25)*	
LABOURMILKMACHINERY	0.016 (0.16)	
LABOUROTHERMACHINERY	0.127 (1.02)	
FEEDVETERINARY	0.013 (0.26)	
FEEDMILKMACHINEREY	0.046 (0.81)	
FEEDOTHERMACHINERY	-0.119 (1.71)*	
VETERINARYMILKMACHINERY	0.029 (0.92)	
VETERINARYOTHERMACHINERY	0.067 (1.50)*	
MILKOTHERMACHINERY	-0.003 (0.05)	
Constant	-0.019 (0.60)	0.000 (0.00)
Observations	293	293
Adjusted R-squared	0.52	0.48
Absolute value of t-statistics in parentheses		
* significant at 5% level; ** significant at 1% level; ^{2}cross-product (squared variable)		

The additional terms are not discussed in further detail, as the main intention here is to test for the preferred functional form. Due to the mean centring procedure explained above, the output elasticities can be seen directly as they are the coefficients of the CD terms. Comparing the TL results with those for the CD, reported in the second column, shows that allowing for non-linearity in the data has considerably increased the elasticity of feed, which was the one variable for which the squared term was significant (and positive).

In terms of the test statistics, the CD has a higher F statistic as the TL is penalised for the large number of extra variables that increase the explanatory power very little. The tests on which the choice of functional form should be based follow, beginning with a log likelihood ratio test. The likelihood-ratio test statistic, λ = -2{log(Likelihood (H_0)) – log(Likelihood (H_1))} has approximately χ^2_v distribution with v equal to the number of parameters assumed to be zero in the null hypodissertation. This produces a value of LR chi^2 (21) = 47.88, which is compared to the values in the table, where it transpires that the critical value for 0.5% confidence is 41.4. Thus, the CD is rejected in favour of the TL, as it is not an adequate representation of the data.

Since the CD model is nested in the TL, it is perhaps more intuitive to use this property more directly and perform a Wald test to see if the 21 extra coefficients can be constrained to zero without damaging the model. This test gives an F(21, 265) = 2.24 and the critical value at the 5% confidence level is 1.87, the null hypothesis that all these coefficients are zero can be soundly rejected. Stata reports this as a probability of 0.0018 that the null hypothesis is true. Thus, for the net outputs model, the TL is preferred to the CD

5.5 Modelling panel data

Pooling the data in the manner of the previous sections increases the sample size, but if no distinction is made between cross section and time series, the estimates are based on less than full information and are also likely to be biased. Thus, the next stage is to specifically allow for the time series and cross sectional aspects of the data in the estimation procedure by fitting panel data models.

5.5.1 Random coefficients and Swamy's model

One of the simplest approaches to go beyond simply pooling the data and ignoring the cross sectional and time dimensions is to take some form of average of the coefficients for the different years, as suggested by Swamy (1970).[12] His estimator uses weights calculated from the variances of the coefficients and the data over the years. The results in Table 24 show the pooled estimates first, followed by the annual estimates. The estimates differ from those above because total feed, which was frequently insignificant, is replaced by purchased feed. The rationale for this change is discussed below. The first set of results are for the entire sample, using the estimator explained by

[12] To run Swamy in Stata, the group is set as time and time as farms, giving the nine groups shown here. Otherwise it would give 37 groups, each with too few observations to give reasonable results.

Greene (1993: 459-62). These results are similar to those reported in Table 19 to 22 above. Other machinery is not significant, but the other five coefficients are significant at the 5% confidence level or better. However, this aggregate model does no better than the simple pooling exercises above, even though the individual year results are rather better than those in Table 18. Indeed, no annual regression has less than three significant elasticities and the total is 33, which is 61%. The test at the top of Table 24 is for the null hypothesis that there is no significant variation in the coefficients and this is soundly rejected, as would be expected since casual perusal shows that there is a great deal of variation.

Table 24: Swamy random coefficients regression

Swamy random-coefficients regression				Number of obs = 293
Group variable (i): year				Number of groups = 9
				Obs per group: min = 22
				avg = 32.6
				max = 37
				Wald chi2(6) = 231.75
				Prob > chi2 = 0.0000
lincomeall	Coef.	Std. Err.	z	P>|z|
lland	0.238717	0.116434	2.05**	0.04
llabourcost	0.180057	0.077107	2.34**	0.02
lpurchasedfeed	0.184417	0.050176	3.68**	0
ltotalvet	0.090907	0.046766	1.94**	0.052
lmilkmachinery	0.087388	0.043387	2.01**	0.044
lothermachinery	0.033068	0.047666	0.69	0.488
_cons	5.027414	0.578776	8.69	0
Test of parameter constancy: chi-squared(56) = 169.2				
Group-specific coefficients				
	Coef.	Std. Err.	z	P>|z|
Group 1				
lland	0.160825	0.130695	1.23	0.218
llabourcost	0.17765	0.095686	1.86**	0.063
lpurchasedfeed	0.308279	0.054924	5.61**	0
ltotalvet	-0.04816	0.04114	-1.17	0.242
lmilkmachinery	0.011278	0.047891	0.24	0.814
lothermachinery	0.160273	0.051673	3.1**	0.002
_cons	5.216548	0.632912	8.24	0
Group 2				
lland	0.084216	0.136626	0.62	0.538
llabourcost	0.109661	0.100194	1.09	0.274
lpurchasedfeed	0.251246	0.058624	4.29**	0
ltotalvet	0.156975	0.062013	2.53**	0.011
lmilkmachinery	0.105068	0.055143	1.91**	0.057
lothermachinery	-0.08539	0.065093	-1.31	0.19
_cons	6.356177	0.685831	9.27	0
Group 3				
lland	0.055642	0.145412	0.38	0.702
llabourcost	0.339745	0.100353	3.39**	0.001
lpurchasedfeed	0.087843	0.056551	1.55*	0.12
ltotalvet	0.096543	0.063128	1.53*	0.126
lmilkmachinery	0.173573	0.051918	3.34**	0.001
lothermachinery	0.015774	0.063461	0.25	0.804
_cons	4.874503	0.682513	7.14	0

Group 4				
lland	0.059448	0.140525	0.42	0.672
llabourcost	0.300431	0.086128	3.49**	0
lpurchasedfeed	0.144992	0.056567	2.56**	0.01
ltotalvet	0.068446	0.045105	1.52*	0.129
lmilkmachinery	0.130153	0.051378	2.53**	0.011
lothermachinery	0.036774	0.052656	0.7	0.485
_cons	5.06404	0.646935	7.83	0
Group 5				
lland	0.389869	0.140853	2.77**	0.006
llabourcost	0.102542	0.099611	1.03	0.303
lpurchasedfeed	0.150734	0.058817	2.56**	0.01
ltotalvet	0.112557	0.059122	1.9**	0.057
lmilkmachinery	0.072574	0.053084	1.37*	0.172
lothermachinery	0.045362	0.064011	0.71	0.479
_cons	4.941209	0.683497	7.23	0
Group 6				
lland	0.446835	0.139824	3.2**	0.001
llabourcost	0.130099	0.101625	1.28*	0.2
lpurchasedfeed	0.159423	0.060536	2.63**	0.008
ltotalvet	0.061748	0.046123	1.34*	0.181
lmilkmachinery	0.090785	0.055708	1.63**	0.103
lothermachinery	0.060611	0.059913	1.01	0.312
_cons	4.570538	0.687008	6.65	0
Group 7				
lland	0.142504	0.14233	1	0.317
llabourcost	0.184484	0.097734	1.89**	0.059
lpurchasedfeed	0.223641	0.063365	3.53**	0
ltotalvet	0.189785	0.063089	3.01**	0.003
lmilkmachinery	0.027139	0.057032	0.48	0.634
lothermachinery	-0.00734	0.06547	-0.11	0.911
_cons	4.946103	0.702595	7.04	0
Group 8				
lland	0.263746	0.140994	1.87**	0.061
llabourcost	0.122763	0.097979	1.25*	0.21
lpurchasedfeed	0.259457	0.063844	4.06**	0
ltotalvet	0.154562	0.061327	2.52**	0.012
lmilkmachinery	-0.01704	0.058284	-0.29	0.77
lothermachinery	0.047724	0.066964	0.71	0.476
_cons	4.740056	0.705633	6.72	0
Group 9				
lland	0.545373	0.160894	3.39**	0.001
llabourcost	0.153137	0.092492	1.66**	0.098
lpurchasedfeed	0.074136	0.055422	1.34*	0.181
ltotalvet	0.02571	0.062191	0.41	0.679
lmilkmachinery	0.192963	0.054269	3.56*	0
lothermachinery	0.023822	0.067733	0.35	0.725
_cons	4.537549	0.693679	6.54	0
** Significant at 5%. * Significant at 10%.				

5.5.2 Panel data models: fixed and random effects with one way error components

The different relationships modelled in this section are not explained in the theory chapter and will be briefly noted here. The most common panel data model is **the one-way error components model**,

$$y_{it} = \beta x_{it} + \partial z_i + u_i + \varepsilon_{it} \tag{5.14}$$

so-called because of the composite error term, in which the u_i are farm specific effects. The z_i are vectors of time invariant variables that vary only across farms in a given year. The fixed effects (**FE**) version of the model treats the u_i as parameters that are farm specific intercepts. The estimator is equivalent to the least squares dummy variables (**LSDV**) model, in which there would be a farm specific intercept dummy for each of the n farms. However, if n is large and the time series is short this may be infeasible, so the estimator in Stata removes all the u_i by mean differencing the data. Baum (2006:221), which this section follows, explains that this transformation will also remove any farm-specific, time-invariant variables (such as gender or soil type), so the z_i are also wiped out by the mean differencing. The random effects model (**RE**) assumes that the u_i in (5) are a random draw and are uncorrelated with ε_{it} and x_{it}. This allows a more efficient estimator, but it is inconsistent if the assumptions are false (Baum, 2006:226-7). This fact forms the basis of the tests to determine if FE or RE is appropriate, which are discussed below.

The results of fitting a CD with random effects for farms in a panel are reported in Table 25, beginning with the decomposition of the overall R^2 into within and between contributions. Baltagi (2005) explains that the between estimator is based on the cross section aspect of the data, while the within estimator uses the time series. The within estimator is defined and explained by Baum (2006:221). This part of the estimation contributes the time series aspect of the data and depends upon the variation around the mean of y and x being correlated for each of the 37 farms. This implies that any variable which does not vary over time will not contribute (say gender of farmer or type of tenancy). Since the maximum time series of observations per group is 9 and the minimum 6, the within estimator should perhaps not be expected to contribute much to the overall R^2 and in this case the within is only 0.1869. The between estimator (BE), which has an R^2 of 0.6051, stems from the correlation of the time series variances of x and y, as it is based on regressing the group means of y on the group means of the x.[13] The overall R^2 is a matrix-weighted average of the between and within R^2s, with weights depending on the relative precision of the two estimators. The attraction is that the source of the explanatory power can easily be seen and in this case the cross section, between farms dimension dominates the time series.

[13] The BE estimator used alone sounds like a good way to average out inconsistencies over time, like the percentage of dry cows, for the individual farms, to give an alternative form of average to compare with the Swamy results above. The BE estimates are not reported here as only two of the six elasticities were positive and significant as compared with five in the Swamy version.

Table 25: Panel with Cobb-Douglas and fixed effects for farms

(within) regression			Number of observation = 293			
Group variable (i): farmid			Number of groups = 37			
Within 0.1869			Observation per group: min = 6			
between 0.6051			average = 7.9			
overall 0.4745			maximum = 9			
			F(7,249) = 8.18			
			Probability > F = 0			
Output*	Coefficient	Standard Error	t	P>|t|	[95% Conf. Interval]	
llandmd	0.231709**	0.08466	2.74	0.007	0.064968	0.398451
llabourmd	0.047524	0.051992	0.91	0.362	-0.05487	0.149924
lfeedmd	0.079757	0.027299	2.92	0.004	0.02599	0.133525
lvetmd	0.031233	0.018752	1.67	0.097	-0.0057	0.068165
lmilkmachinerymd	0.024044	0.023204	1.04	0.301	-0.02166	0.069744
lothermachinerymd	0.030562	0.0285	1.07	0.285	-0.02557	0.086693
ldrycows	-0.00776	0.002216	-3.5	0.001	-0.01213	-0.0034
constant	0.138307	0.041475	3.33	0.001	0.056621	0.219994
sigma_u	0.294001					
sigma_e	0.217934					
rho	0.645377 (fraction of variance due to u_i)					
F test that a u_i=0:		F(36, 249) =10.39			Probability >F = 0.0000	
**significant at 5% level						

*=milk output deflated and mean differenced

The null hypodissertation for the F test is that $u_i = 0$, as in equation (5) and this is clearly rejected, meaning that there are fixed effects and OLS on the pooled sample, as used in section 4.3 above, is not adequate. The results are actually worse than for pooled OLS, as the R^2 is lower and three of the four elasticities are not significant. However, there is little point in trying to improve this model as FE needs to be tested against RE and the CD against the TL.[14] The RE model results are in Table 26, which fits slightly better than the FE model, but most obviously, all six of the elasticities are significant. This suggests that there may be time invariant, farm specific components of labour and the two machinery variables that were lost in the mean differencing approach of the FE model. The most obvious weakness of this model is that the sum of the elasticities (0.56) is so far below unity that it suggests misspecification (in the sense of omitted inputs) rather than decreasing returns to scale. The last three statistics in the table show that u_i has a greater variance than ε_i, indeed accounting for over half the total variance. As pooled OLS is optimal if $\sigma^2_u = 0$, this suggests that OLS is not appropriate in this case. The Lagrange multiplier test of Breusch and Pagan and Hall (1983), for which the null is that $\sigma^2_u = 0$, gives Chi square (1) = 190.52, against a critical value at 5% of 3.84, so there is no doubt that the FE or RE model is preferred.[15]

[14] The test for the RE versus FE models follows shortly.
[15] In Stata this is the post regression command xttest0, used after the RE regression.

Table 26: Panel with Cobb-Douglas and random effects for farms

Random-effect GLS regression			Number of observation = 293			
Group variable (i): farmid			Number of groups = 37			
Within 0.1852			Observation per group: min = 6			
Between 0.6169			average = 7.9			
overall 0.4841			maximum = 9			
Random effect u_i ~ Gaussian = 0 (assumed)			Wald $chi^2(7)$ = 102.03			
			Probability > chi-squared = 0			
qdmd	Coefficient	Standard Error	z	P>|z|	[95% Conf.	Interval]
llandmd	0.286658**	0.076034	3.77	0	0.137635	0.435681
llabourmd	0.073159	0.050557	1.45	0.148	-0.02593	0.172248
lfeedmd	0.089221	0.027321	3.27	0.001	0.035674	0.142768
lvetmd	0.040105	0.018849	2.13	0.033	0.003162	0.077048
lmilkmachinerymd	0.033087	0.022714	1.46	0.145	-0.01143	0.077605
lothermachinerymd	0.036537	0.027731	1.32	0.188	-0.01781	0.090888
ldrycows	-0.00789	0.002189	-3.61	0	-0.01218	-0.0036
constant	0.127431	0.05641	2.26	0.024	0.01687	0.237992
sigma_u	0.230546					
sigma_e	0.217934					
rho	0.5281 (fraction of variance due to u_i)					
**Significant level						

The FE and RE models are compared using a Hausman test (Baum, 2006) which tests for the orthogonality of the u_i and the regressors by comparing the estimated coefficients of the FE and RE models. Baum (2006:230-31) explains that if the orthogonality assumption is violated, the inconsistent RE estimates will differ significantly from the FE estimates. Thus, the null hypodissertation is that the difference is not systematic and RE can be accepted as the preferred estimator. The test results are reported in full in Table 27, which ultimately gives a Chi square (7) statistic of 14.14, which is compared with a 5% critical value of 14.067. Thus, the RE model should be rejected in favour of the FE model, which would be most unfortunate. Luckily, this difficult decision is avoided, as the next step is to test for the adequacy of the functional form, by comparing the CD and the TL.

The TL results for the FE version of this model follow the CD, in that the FE model has three insignificant coefficients, whereas only other machinery is insignificant for the RE model. This does not matter as the Hausman test clearly selects the RE model and the Breusch and Pagan (1980) test shows that $\sigma^2_u = 0$ is clearly rejected.[16] This model is not reported, as it is possible to improve the model significantly by experimenting with the alternative output deflation methods and by lagging variables one period, as was done with veterinary expenses above, in Section 5.3. The output variable used so far, in which product income was deflated with the fresh milk deflator,

[16] The Hausman test is explained in discussion of the results in Table 29, which follows shortly.

proves to give the worst results with this more tightly fitting model. It also has a negative coefficient on time, of 0.043, once the year is included. This would mean negative technical progress at a rate of 4.3% per annum. Not only does this seem unlikely, but if the milk price is held constant by using the 2001 prices throughout, or by using litres of milk, this changes to plus about 2% per year, which seems much more likely. This would indicate that the national fresh milk price deflator over-deflates the output for the farms in this region, as the other two methods really are imposing constant prices and are closer to giving the physical quantities required in production function analysis.

Table 27: Hausman test for fixed versus random effects

coefficients	(b)	(B)	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E
llandmd	0.286658**	0.231793**	0.054949	.
llabourmd	0.073159	0.0475244	0.025634	.
lfeedmd	0.089221	0.0797574	0.009463	0.001729
lvetmd	0.040105	0.0312331	0.008872	0.001912
lmilkmachinerymd	0.033087	0.02444	0.009043	.
lothermachinerymd	0.036537	0.030562	0.005975	.
ldrycows	-0.00789	-0.0077647	-0.000128	.
b = consistent under Ho and Ha; obtained from xtreg				
B Is inconsistent under Ha, efficient under Ho; obtained from xtreg				
Test: Ho difference in coefficients not systematic				
chi-squared(7) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 14.14				
Probability>chi2 = 0.0487				
(V_b-V_B is not positive definite)				
**Significant at the 5% level				

Table 28 reports the TL results using milk in litres at the 2001 average price in the output variable. This does not take account of quality differences between farms, but this may be preferable to a deflator that is not correct. The u_i accounts for almost half the variance, so it is not surprising that OLS can be dismissed as an alternative. Similarly the null hypothesis that all the squared and cross product terms are zero is rejected as the statistic for the Wald test is 57.64, which is outside the acceptance region even at the .005 confidence level. Thus, the TL is preferred to the CD.

Table 28: Translog panel with random effects for farms

Random-effects GLS regression				Number of observations = 256	
Group variable (i): farmid				Number of groups = 37	
R-squared: within = 0.5994				Observations per group: min = 5	
between = 0.7553				average = 6.9	
overall = 0.6973				maximum = 8	
Random effects u_i ~ Gaussian corr(u_i, X) = 0 (assumed)				Wald chi-squared(29) = 392.53	
				Probability > chi-squared = 0.0000	
loutputmd	Coefficient	Standard Error	z	P>|z|	[95% Conf. Interval]
llandmd	0.250014**	0.064555	3.87	0	.1234889 .3765387
llabourmd	0.163875*	0.048432	3.38	0.001	.0689504 .2587996
lfeedmd	0.120454*	0.030763	3.92	0	.0601604 .1807474
lvetmd	0.050019	0.015133	3.31	0.001	.0203591 .0796796
lmilkmachinerymd	0.048213	0.018569	2.6	0.009	.0118175 .0846079
lothermachinerymd	0.04989	0.02175	2.29	0.022	.0072614 .0925182
llandmd^2	-0.07629	0.145939	-0.52	0.601	-.3623307 .209741
llabourmd^2	-0.04377	0.046673	-0.94	0.348	-.1352441 .0477101
lfeedmd^2	0.016512	0.011274	1.46	0.143	-.0055843 .0386087
lvetmd^2	-0.01789	0.011618	-1.54	0.124	-.0406601 .0048813
lmilkmachinerymd^2	-0.00933	0.013437	-0.69	0.487	-.0356702 .0170008
lothermachinerymd^2	0.008773	0.014114	0.62	0.534	-.0188902 .0364357
landlabour	-0.01222	0.157006	-0.08	0.938	-.319942 .2955104
landfeed	-0.20921	0.102529	-2.04	0.041	-0.41842
landvet	-0.02924	0.053228	-0.55	0.583	-.1335649 .0750836
landmilkmachinery	0.18332	0.060505	3.03	0.002	.0647331 .3019077
landothermachinery	0.004786	0.074118	0.06	0.949	-.1404829 .1500553
labourfeed	0.042307	0.075038	0.56	0.573	-.1047647 .1893782
labourvet	0.017922	0.044988	0.4	0.69	-.0702528 .1060976
labourmilkmachinery	-0.01779	0.049888	-0.36	0.721	-.115574 .0799846
labourothermachinery	0.065138	0.077152	0.84	0.399	-.0860762 .2163529
feedvet	0.037193	0.033777	1.1	0.271	-.02901 .1033952
feedmilkmachinery	-0.084	0.029138	-2.88	0.004	-0.168
feedothermachinery	0.074379	0.048704	1.53	0.127	-.0210792 .1698366
vetmilkmachinery	0.029342	0.017566	1.67	0.095	-.0050858 .0637699
vetotthermachinery	-0.021	0.023767	-0.88	0.377	-.0675868 .0255787
milkothermachniery	-0.00701	0.025063	-0.28	0.78	-.05613 .0421147
drycows	-0.00637	0.001741	-3.66	0	-0.01274
year	0.022216	0.006428	3.46	0.001	.0096185 .0348139
_cons	-44.3862	12.87507	-3.45	0.001	-88.7724
sigma_u	0.12856				
sigma_e	0.146855				
rho	0.433867	(fraction of variance due to u_i)			
**Significant at the 5% level; *significant at the 10% level					

The first improvement is a Wald statistic almost four times as large, followed by a huge improvement in the overall R^2, indicating that 70% of the variance is now explained. This is mostly attributable to the similar increase in the within estimator, which is now contributing almost as much as the between estimator. All the variables are now highly significant, even other machinery, now that it is lagged one period. This suggests that much of the effect of tractor use is not felt until the following year, which would be the case for work like land preparation, to grow fodder for the next season. Note that the lagging procedure reduces the sample size by 37, as one observation is lost for each farm. The weakest point of these estimates remains the low sum of the elasticities. This is 0.72, which still may suggest omitted inputs. The RE model must also be compared with the FE model. The RE model has better results and since the Hausman test accepted the RE model, the FE results are not reported. The Hausman test, in the last rows of Table 29 shows that the hypodissertation of no systematic difference in FE and RE coefficients can be accepted as the Chi square is 9.33 and would have to be over 40 for rejection.

Table 29: Hausman test for RE versus FE for a translog

hausman re1				
	Coefficients			
	(b) re1	(B)	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
louputmd	0.250014	0.1353545	0.114659	.
llandmd	0.163875	0.153941	0.009971	0.003106
llabourmd	0.120454	0.1017146	0.018739	0.006103
lfeedmd	0.050019	0.0434881	0.006531	0.005067
lvetmd	0.048213	0.0132258	0.034987	.
lmilkmachinerymd	0.04989	0.033447	0.016485	0.003412
lothermachinerymd	-0.07629	-0.0292258	-0.04707	.
llandmd2	-0.04377	-0.023736	-0.02003	0.016207
llabourmd2	0.016512	0.01715	0.005797	0.003625
lfeedmd2	-0.01789	-0.021589	0.0037	0.003604
lvetmd2	-0.00933	-0.0253784	0.016044	.
lmilkmachinerymd2	0.008773	-0.0000552	0.009325	0.004394
lothermachinerymd2	-0.01222	-0.0335133	0.021298	0.044191
landlabour	-0.20921	-0.22258	0.010817	0.031974
landfeed	-0.02924	0.0246644	-0.05391	0.011488
landvet	0.18332	0.1486273	0.034693	.
landmilkmachinery	0.004786	0.0281878	-0.0234	.
landothermachinery	0.042307	0.035776	0.006599	0.026201
labourfeed	0.017922	0.0014135	0.016509	0.015413
labourvet	-0.01779	0.024993	-0.04189	.
labourmilkmachinery	0.065138	0.0329217	0.032217	0.024305
labourothermachinery	0.037193	0.0438643	-0.00667	0.011157
feedvet	-0.084	-0.10231	0.018006	0.009744
feedmilkmachinery	0.074379	0.0762592	-0.00188	0.013795
feedothermachinery	0.029342	0.0338366	-0.00449	0.005456
vetmilkmachinery	-0.021	-0.0246143	0.00361	0.007945
vetotthermachinery	-0.00701	-0.0171793	0.010172	.
milkothermachniery	-0.00637	-0.005594	-0.00078	.
drycows	0.022216	0.0311413	-0.00893	0.000776
b = consistent under Ho and Ha; obtained from xtreg				
B = consistent under Ha, efficient under Ho; obtained from xtreg				
Test: Ho: difference in coefficients not systematic chi2(29) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 9.33				
Prob>chi2 = 0.9998 (V_b-V_B is not positive definite)				

Table 30 shows the results of the TL panel with fixed effects with number of cows.

Table 30: Translog panel with fixed effects for farms with cows

Fixed-effects (within) regression				Number of observations = 256			
Group variable (i): farmid				Number of groups = 37			
R-square: within = 0.6762				Observations per group: min = 5			
between = 0.6398				average = 6.9			
overall = 0.6184				maximum = 8			
				F(37,182) = 10.27			
corr(u_i, Xb) = 0.3314				Probability >F = 0			
Output	Coefficient	Standard Error	t	P>|t|	[95% Conf	Interval]	
land	0.107561**	0.082578	1.3	0.194	-0.05537	0.270495	
labour	0.111605*	0.047776	2.34	0.021	0.01734	0.205871	
feed	0.10324*	0.031243	3.3	0.001	0.041596	0.164885	
vet^{-1}	0.045472	0.01397	3.25	0.001	0.017908	0.073036	
milkmachinery	-0.00423	0.018352	-0.23	0.818	-0.04044	0.031983	
othermachinery1	0.011721	0.021076	0.56	0.579	-0.02986	0.053304	
lcowsmd	0.137122	0.101654	1.35	0.179	-0.06345	0.337695	
land^{2}	0.046393	0.164204	0.28	0.778	-0.27759	0.37038	
labour^{2}	-0.01305	0.051616	-0.25	0.801	-0.11489	0.088796	
feed^{2}	0.010134	0.013623	0.74	0.458	-0.01675	0.037014	
vet1^{2}	-0.0181	0.010634	-1.7	0.09	-0.03908	0.002885	
milkmachinery^{2}	-0.01911	0.014453	-1.32	0.188	-0.04762	0.009411	
othermachinery1^{2}	0.008027	0.013903	0.58	0.564	-0.0194	0.035458	
cows^{2}	0.834194	0.216415	3.85	0	0.40719	1.261199	
landxlabour	0.044148	0.159327	0.28	0.782	-0.27022	0.358515	
landxfeed	-0.18747	0.100789	-1.86	0.064	-0.38634	0.011395	
Landxvet^{-1}	0.018681	0.05146	0.36	0.717	-0.08285	0.120215	
landxmilkmachinery	0.087504	0.066114	1.32	0.187	-0.04294	0.217953	
landxothermachinery^{-1}	0.026146	0.081138	0.32	0.748	-0.13395	0.186237	
labourxfeed	-0.02166	0.082562	-0.26	0.793	-0.18456	0.141241	
labourxvet^{-1}	0.014666	0.045341	0.32	0.747	-0.0748	0.104128	
labourxmilkmachinery	0.018454	0.054819	0.34	0.737	-0.08971	0.126616	
labourxothermachinery^{-1}	0.075435	0.075219	1	0.317	-0.07298	0.223849	
feedxvet^{-1}	0.048195	0.031948	1.51	0.133	-0.01484	0.111232	
feedxmilkmachinery	-0.12549	0.029156	-4.3	0	-0.18302	-0.06796	
feedxothermachinery^{-1}	0.071361	0.046957	1.52	0.13	-0.02129	0.16401	
vet^{-1}xmilkmachinery	0.030637	0.016003	1.91	0.057	-0.00094	0.062211	
vet^{-1}xothermachinery^{-1}	-0.03547	0.022766	-1.56	0.121	-0.08038	0.009453	
milkmachineryxothermachinery^{-1}	-0.01375	0.026806	-0.51	0.609	-0.06664	0.039136	
cowsland	-0.36848	0.24541	-1.5	0.135	-0.8527	0.115731	
cowslabour	-0.24688	0.20822	-1.19	0.237	-0.65771	0.163956	
cowsfeed	-0.04716	0.141569	-0.33	0.739	-0.32649	0.232166	
cowsvet	-0.06254	0.06623	-0.94	0.346	-0.19321	0.06814	
cowsmilkmachinery	0.027103	0.100206	0.27	0.787	-0.17061	0.224818	
cowsothermachinery	-0.05393	0.087215	-0.62	0.537	-0.22601	0.118156	
drycows	-0.00733	0.001757	-4.17	0	-0.0108	-0.00386	
years	0.031063	0.006923	4.49	0	0.017403	0.044724	
_cons	-62.1238	13.87246	-4.48	0	-89.4953	-34.7523	
sigma_u	0.243363						
sigma_e	0.138525						
rho	0.755287 (fraction of variance due to u_i)						
F test that all u_i=0: F(36, 182) = 8.03 Prob > F = 0.0000							
**Significant at the 5% level; *10% level; $^{-1}$= lagged one year; ^{2}= squared; x= cross-product							

The results are substantially improved by adding cows with a much higher R-square (0.62 compared with 0.48) and Wald chi-squared (37) of 810.61 compared with a Wald chi-squared (29) of 392.53 in Table 29. A similar picture is depicted in Table 31 which shows TL with random effects with cows included. The R-square and the Wald chi-square statistics are substantially increased by including cows as a variable. Looking at the overall R-square for the random effects with cows as reported in Table 31 shows that there is an improvement of more than 0.17 (17%) over the fixed effects model with cows shown in Table 30 (0.62 and 0.79, respectively). The inclusion of cows can be viewed as taking farm size into cognisance. Again the Wald chi-square (37) of 810.61 is outside the acceptance region even at the .005 confidence level. Thus, the TL is preferred to the CD. The inclusion of cows also addresses the weakness observed when cows were not included in that the elasticities now sum to 1.0 instead of just about 0.62 which may suggest that no variables have been omitted thus the model has been correctly specified and estimated.

The last three statistics in Table 31 show that ε_i has a greater variance than u_i, thus the fraction of variance due to u_i is 0 indicating that most of the variation between farms is not random. This seems to suggest that the differences are largely due to differences in efficiency which will be discussed in the next chapter.

The next logical step is to perform the Hausman test for the fixed effects versus the random effects TL models with cows. The FE and RE models are compared using a Hausman test (Baum, 2006) which tests for the orthogonality of the u_i and the regressors by comparing the estimated coefficients of the FE and RE models as already discussed. The null hypodissertation is that the difference is not systematic and RE can be accepted as the preferred estimator. The test results are reported in full in Table 32 which ultimately gives a Chi square (7) statistic of 3.28, which is compared with a 5% critical value of 49.802 (35 degrees of freedom). Thus, the FE model should be rejected in favour of the RE model. Thus, the preferred model has the results reported in Table 31.

Table 31: Translog panel with random effects for farms with cows (mean differenced)

Random-effect GLS regression				Number of observations = 256		
Group variabl(i): farmid				Number of groups = 37		
R-square:within = 0.5673				Observations per group: min = 5		
between = 0.8748				average = 6.9		
overall = 0.7881				maximum = 8		
Random effect u_i ~ Gaussian				Wald chi-square(37) = 810.61		
corr(u_i, X) = 0 (assumed)				Probability >chi-square = 0		
output	Coefficient	Standard Error	z	P>|z|	[95% Conf	. Interval]
land	0.135459**	0.061035	2.22	0.026	0.015832	0.255085
labour	0.075962	0.051972	1.46	0.144	-0.0259	0.177825
feed	0.109924*	0.039892	2.76	0.006	0.031737	0.188111
vet^{-1}	0.046915	0.01838	2.55	0.011	0.01089	0.082939
milkmachinery	0.080117	0.020315	3.94	0	0.040301	0.119934
othermachinery^{-1}	0.033524	0.025867	1.3	0.195	-0.01717	0.084222
lcows	0.514292**	0.083676	6.15	0	0.35029	0.678295
land^{2}	-0.27682	0.168239	-1.65	0.1	-0.60657	0.052918
labour^{2}	-0.07355	0.067489	-1.09	0.276	-0.20582	0.058729
feed^{2}	0.005193	0.016316	0.32	0.75	-0.02678	0.037171
vet^{2}	-0.02763	0.014012	-1.97	0.049	-0.05509	-0.00017
milkmachinery^{2}	-0.00117	0.015275	-0.08	0.939	-0.03111	0.028769
othermachinery1^{2}	0.014826	0.017279	0.86	0.391	-0.01904	0.048693
cows^{2}	-0.05165	0.229671	-0.22	0.822	-0.5018	0.398496
landxlabour	-0.14978	0.207307	-0.72	0.47	-0.5561	0.256532
landxfeed	-0.26967	0.132699	-2.03	0.042	-0.52976	-0.00959
landxvet^{-1}	-0.03849	0.066288	-0.58	0.561	-0.16842	0.091428
landxmilkmachinery	0.217128**	0.064269	3.38	0.001	0.091163	0.343093
landxothermachinery^{-1}	0.088144	0.081063	1.09	0.277	-0.07074	0.247024
labourxfeed	-0.05569	0.108655	-0.51	0.608	-0.26864	0.157273
labourxvet^{-1}	-0.00566	0.05983	-0.09	0.925	-0.12293	0.111601
labourxmilkmachinery	-0.0014	0.064482	-0.02	0.983	-0.12778	0.124987
labourxothermachinery^{-1}	0.083367	0.095888	0.87	0.385	-0.10457	0.271303
feedxvet^{-1}	0.055074	0.042114	1.31	0.191	-0.02747	0.137615
feedxmilkmachinery	-0.04704	0.037699	-1.25	0.212	-0.12092	0.026854
feedxothermachinery^{-1}	0.051954	0.061997	0.84	0.402	-0.06956	0.173465
vet^{-1}milkmachinery	0.009403	0.021015	0.45	0.655	-0.03178	0.050591
vet^{-1}xothermachinery^{-1}	-0.00981	0.029594	-0.33	0.74	-0.06782	0.048189
milkmachineryxothermachinery^{-1}	0.005426	0.030315	0.18	0.858	-0.05399	0.064842
cowsxland	0.263283	0.254704	1.03	0.301	-0.23593	0.762493
cowsxlabour	0.310927	0.261508	1.19	0.234	-0.20162	0.823474
cowsxfeed	0.191845	0.183192	1.05	0.295	-0.16721	0.550895
cowsxvet	-0.01273	0.083574	-0.15	0.879	-0.17653	0.151075
cowsxmilkmachinery	-0.19535	0.101827	-1.92	0.055	-0.39493	0.004229
cowsxothermachinery	-0.06169	0.101981	-0.6	0.545	-0.26157	0.138187
drycows	-0.00923	0.002019	-4.57	0	-0.01318	-0.00527
years	-0.00158	0.007605	-0.21	0.835	-0.01649	0.013325
constant	3.35033	15.23983	0.22	0.826	-26.5192	33.21984
sigma_u	0					
sigma_e	0.138525					
rho	0 (fraction of variance due to u_i)					
**Significant at the 5% level; *significant at 10% level; $^{-1}$ = variable lagged one period;^{2} = variable squared; x=cross product						

The error components model in Stata is one way, meaning that only the farm specific component is taken into account and not the time dimension. Baum (2006: 224-6) shows how the time dimension can be incorporated as dummy variables, in a manner that amounts to extending the Stata estimator to a two way error components model. Above, we simply added the time variable to the x_i as an explanatory variable as this allows the coefficient on time to be interpreted as the rate of technological change. This was done earlier in this section, after the Table 26 results for the CD, where technological improvement appeared to be increasing efficiency at about 2% per annum. The result for time in Table 25 is essentially the same, in that the coefficient on time can be interpreted as meaning that efficiency increases at 2.22% per annum over time. This is frequently interpreted as technological change, but it could be caused by this and/or any other time-related variables.

5.5.3 Two-way error components

The results in Table 32 are for the last one-way error components model and the introduction of the time aspect is appropriate, as this section explicitly models both the individual and time aspects as a two-way error components model. Following Baltagi (2005), in the previous case, if we ignore the z variable that was included in Equation (5.15) to show the effects of mean differencing for the FE model, simply resulting in equation (5.16), in which there are regressors and an error term. This error is divided into components in equation (5.17), which are the unobservable farm-specific effects and a remaining random error. Now, equation (5.18) shows that for the two-way error components model thus simply allowing also for unobservable time effects, denoted by λ_t.

$$y_{it} = \beta x_{it} + E_{it} \qquad \textbf{(5.15)}$$

One-way error components model (farm only)

$$E_{it} = u_i + \varepsilon_{it} \qquad \textbf{(5.16)}$$

Two-way error components model (farm and time)

$$E_{it} = u_i + \lambda_t + \nu_{it} \qquad \textbf{(5.17)}$$

Table 32: Hausman test for FE Versus RE for a translog with cows (mean differenced)

hausman fe1	coefficients			
	(b) fe1	(B)	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
land	0.107561	0.1354585	-0.027897	0.0556224
labour	0.111605	0.0759624	0.035643	.
feed	0.10324	0.109924	-0.006684	.
vet^{-1}	0.045472	0.0469149	-0.001443	.
milkmachinery	-0.00423	0.0801174	-0.084345	.
$othermachinery^{-1}$	0.011721	0.0335237	-0.0218	.
lcows	0.137122	0.5142922	-0.37717	0.0577224
$land^2$	0.046393	-0.276824	0.323217	.
$labour^2$	-0.01305	-0.073558	0.060502	.
$feed^2$	0.010134	0.0051933	0.00494	.
vet^2	-0.0181	-0.027635	0.009533	.
$milkmachinery^2$	-0.01911	-0.001176	-0.017937	.
$othermachinery^2$	0.008027	0.0148259	-0.006799	.
$cows^2$	0.834194	-0.051655	0.885844	.
landxlabour	0.044148	-0.149782	0.193932	.
landxfeed	-0.18747	-0.269674	0.082203	.
$Landxvet^{-1}$	0.018681	-0.038496	0.057176	.
landxmilkmachinery	0.087504	0.2171279	-0.129624	0.0155097
$landxotthermachinery^{-1}$	0.026146	0.0881437	-0.061998	0.0034892
labourxfeed	-0.02166	-0.055696	0.034026	.
$labourxvet^{-1}$	0.014666	-0.005664	0.02033	.
labourxmilkmachinery	0.018454	-0.00147	0.019849	.
$labourxothermachinery^{-1}$	0.075435	0.0833666	-0.007932	.
$feedxvet^{-1}$	0.048195	0.0550738	-0.006878	.
feedxmilkmachinery	-0.12549	-0.047044	-0.078455	.
$feedxothermachinery^{-1}$	0.071361	0.0519542	0.019406	.
$vet^{-1}xmilkmachinery$	0.030637	0.0094031	0.021234	.
$vet^{-1}xothermachinery^{-1}$	-0.03547	-0.009815	-0.025651	.
$milkmachineryxothermachinery^{-1}$	-0.01375	0.0054259	-0.01918	.
cowsxland	-0.36848	0.2632828	-0.631767	.
cowsxlabour	-0.24688	0.3109269	-0.557805	.
cowsxfeed	-0.04716	0.1918447	-0.23901	.
cowsxvet	-0.06254	-0.012739	-0.049811	.
cowsxmilkmachinery	0.027103	-0.195352	0.222452	.
cowsxothermachinery	-0.05393	-0.061698	0.007767	.
drycows	-0.00733	-0.009226	0.001898	.
years	0.031063	-0.001585	0.032645	.
b = consistent under Ho and Ha; obtained from xtreg				
B = consistent under Ha, efficient under Ho; obtained from xtreg				
Test: Ho: difference in coefficients not systematic				
chi2(37) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 3.28				
Prob>chi2 = 1.0000 (V_b-V_B is not positive definite)				

Nlogit (or Limdep) models this estimator explicitly and gives more detailed output, since rather than mean differencing to remove the farm effects it models the time effect with dummies. The estimator for FE is described in the manuals as LSDV (StataCorp, 2007), as indeed it used both farm and time- dummies, instead of mean differencing to remove the farm-specific dummies, as Stata does. The random effects model is synonymous with error components and the attraction is that Limdep models equation (5.17) and produces an impressive array of outputs. Since the arguments and tests to determine the preferred models have been developed over the previous sections, it is possible to show just the preferred model, but this is done step by step, as the estimators differ enough to give somewhat different results. The preferred model is that with milk in litres (output) as part of the dependent variable and with labour measured as cost in constant terms. This is the same as for the preferred one-way error components models above.

The first step in Limdep is to estimate and report the pooled OLS results. The results in Table 33 can be compared with those in Table 15, where it is apparent that variable selection and lagging veterinary expenses and tractors has considerably improved the fit of the OLS model. The R^2 has increased from 0.49 to 0.69, which is a good level of explanatory power for data that is predominantly cross sectional. The arrays of test statistics are not really comparable and better models follow. Note that only the direct terms are reported in Table 33, as the other terms add very little in these mean differenced models. In all these cases tests show that the CD is not an adequate representation of the data, so only the TL results are reported.

Table 33: Results of the Pooled OLS

OLS Without Group Dummy Variables Ordinary least squares regression				
LHS=OUTPUTMD Mean = .8118506E-15				
Standard deviation = .4089062				
WTS=none Number of observations = 256				
Model size Parameters = 29				
Degrees of freedom = 227				
Residuals Sum of squares = 11.73014				
Standard error of e = .2273205				
Fit R-squared = .7248842 Adjusted R-squared = .6909492				
Model test F[28, 227] (probability) = 21.36 (.0000)				
Diagnostic Log likelihood = 31.37779				
Restricted(b=0) = -133.8143				
Chi-squared [28] (probability) = 330.38 (.0000)				
Info criter. LogAmemiya Prd. Crt. = -2.855477				
Akaike Info. Criter. = -2.856454				
Variable	Coefficient	Standard Error	t -ratio	P[T>t]
LANDMD	0.287377**	0.05818	4.939	.0000
LABOURMD	0.177844*	0.052331	3.398	.0008
FEEDMD	0.16372	0.037039	4.42	.0000
$VETMD^{-1}$	0.052378	0.019906	2.631	.0091
MILKMACHINERYMD	0.116426	0.021606	5.389	.0000
$OTHERMACHINERYMD^{-1}$	0.02812	0.027934	1.007	.3152

The next stage in the Limdep procedure is to estimate the LSDV version of the same one-way error components models that concluded the last section. This model is not reported because the results are too similar to the Stata version. The final Limdep model is the two-way error components model. Table 34 begins by showing that the RE model is accepted, as the critical Chi square value is 41.34. Thus, only the RE model is reported. The upper part of the table reports the random effects and the lower part reports the comparison between the random and fixed effects. The RE model is accepted because the Hausman test gives a lower value (34.05 compared with 41.34) which favours the RE against the FE.

Table 34: Hausman test for RE versus FE for a translog

Random Effects Model: v(i,t) = e(i,t) + u(i) + w(t)
Estimates: Var[e] = .220478D-01
Var[u] = .566795D-01
Corr[v(i,t),v(i,s)] = .719948
Var[w] = .344469D-02
Corr[v(i,t),v(j,t)] = .135126
Lagrange Multiplier Test vs. Model (3) = 121.43 (2 df, prob value = .000000) (High values of LM favor FEM/REM over CR model.)
Fixed vs. Random Effects (Hausman) = 34.05 (28 df, prob value = .199159) (High (low) values of H favor FEM (REM).)

The two-way error components model, reported in Table 35, like the one way model, has all six elasticities highly significant, but they add to only 0.64, which is exceptionally low. Again, the CD is an inadequate representation of these data, so the TL RE model is selected. The choice between models within this class and the explanatory power of the components is covered in Table 36 beginning with the test statistics for a model that only includes the constant term. Obviously, this has an R-square = 0. The regressors (exogenous variables) explain 72% of the variance and farm specific dummies explain 75%. Then, the tests show a far better log likelihood for the combination of the Xs and farm dummies, which explain 89%. Finally, the combination of the Xs, the farm dummies and the time effects explain over 90% of the variance and have the highest log likelihood statistic. The χ^2 tests that follow these results show that the final model is preferred.

Table 35: Translog panel with random effects for farms and time (mean differenced)

Variable	Coefficient	Standard Error	b /St.Er.	P[|Z|>z]
LAND	0.199675**	0.071548	2.791	.0053
LABOUR	0.190655**	0.046059	4.139	.0000
FEED	0.113023**	0.030149	3.749	.0002
VET^{-1}	0.041312*	0.017221	2.399	.0164
MILKMACHINERY	0.041518*	0.018515	2.242	.0249
$OTHERMACHINERY^{-1}$	0.054547*	0.021012	2.596	.0094
$LAND^2$	-0.03041	0.146926	-0.207	.8360
$LABOUR^2$	-0.0395	0.04425	-0.893	.3720
$FEED^2$	0.015583	0.01073	1.452	.1464
VET^2	-0.01756	0.012217	-1.437	.1506
$MILKMACHINERY^2$	-0.01615	0.013414	-1.204	.2286
$OTHERMACHINERY^2$	0.009492	0.013758	0.69	.4902
LANDxLABOUR	-0.06203	0.150594	-0.412	.6804
LANDxFEED	-0.17537	0.097526	-1.798	.0722
$LANDxVET^{-1}$	-0.00324	0.051717	-0.063	.9501
LANDxMILKMACHINERY	0.195951	0.060964	3.214	.0013
$LANDxOTHERMACHINERY^{-1}$	0.002062	0.075446	0.027	.9782
LABOURxFEED	0.048494	0.070697	0.686	.4927
$LABOURxVET^{-1}$	0.02252	0.042774	0.527	.5985
LABOURxMILKMACHINERY	-0.01376	0.048879	-0.281	.7784
LABOURxOTHERMACHINERY	0.030461	0.073613	0.414	.6790
FEEDxVET	0.03403	0.032509	1.047	.2952
FEEDxMILKMACHINERY	-0.09069	0.027677	-3.277	.0010
$FEEDxOTHERMACHINERY^{-1}$	0.080468	0.04688	1.716	.0861
$VETxMILKMACHINERY^{-1}$	0.027412	0.016951	1.617	.1058
$VETxOTHERMACHINERY^{-1}$	-0.02075	0.022959	-0.904	.3662
$MILKxOTHERMACHINERY^{-1}$	-0.00821	0.024896	-0.33	.7417
DRYCOWS	-0.00576	0.001722	-3.343	.0008
Constant	0.116048	0.059645	1.946	0.0517
**Significant at the 5% level; *Significant at the 10% level; $^{-1}$Lagged one period; ^{2}Squared				

Table 36: Testing for the correct model

Test Statistics for the Classical Model								
Model		Log-likelihood		Sum of Squares		R-squared		
(1) Constant term only		-133.81427		.4263708157D+02		.0000000		
(2) Group effects only		42.12959		.1078507179D+02		.7470495		
(3) X - variables only		31.37780		.1173013689D+02		.7248842		
(4) X and group effects		150.88432		.4611331571D+01		.8918469		
(5) X and time effects		167.28433		.4056788025D+01		.9048531		
Hypodissertation Tests								
Likelihood Ratio Test				F Tests				
	Chi-squared	degree of freedom	Probability	F	numerator	denominator	Probability value	
(2) vs (1)	351.888	36	.00000	17.966	36	219	.00000	
(3) vs (1)	330.384	28	.00000	21.361	28	227	.00000	
(4) vs (1)	569.397	64	.00000	24.610	64	191	.00000	
(4) vs (2)	217.509	28	.00000	9.133	28	191	.00000	
(4) vs (3)	239.013	36	.00000	8.191	36	191	.00000	
(5) vs (4)	32.800	7	.00003	3.593	7	184	.00119	
(5) vs (3)	271.813	44	.00000	7.910	44	184	.00000	

Given that Limdep estimates dummy variables for the farm and time effects it also reports these as Table 37 shows. These should be interpreted as follows. The constant term in the regression, 0.116 in Table 35 above, is the model intercept. Then, the individual intercepts in Table 37 should be used to adjust the model constant. A similar approach should be followed with the interpretation of the time effects. To the extent that this model tries to compare efficiencies between farms, higher values of the intercept adjustment indicate relatively efficient farms; that is, farm 1 appears to be particularly efficient whereas farm 4 is well below the average. This is a similar approach to corrected OLS but this relatively crude measure of efficiency will be avoided as stochastic frontier models are about to be estimated. If interpreted in the same way, the time effects suggest some improvement over the period, which could be attributed to technological change. For this reason the time trend is omitted from the two way error components model.

Table 37: Farm and Time Estimated Parameters

Estimated Fixed Effects – Full sets of effects, normalized to sum to 0			
Farm effects	**Coefficient**	**Standard Error**	**t-ratio**
1	0.34433	0.07575	4.54572
2	0.04847	0.06932	0.69919
3	-0.12114	0.06814	-1.77792
4	-0.45051	0.07389	-6.09706
5	-0.23605	0.08755	-2.69631
6	0.52843	0.2338	2.26017
7	0.12678	0.06343	1.99892
8	-0.04792	0.07125	-0.6726
9	0.05167	0.06927	0.74589
10	-0.12433	0.08623	-1.44175
11	0.04531	0.07915	0.57242
12	0.30734	0.13086	2.34861
13	0.01957	0.07558	0.25887
14	-0.03188	0.07375	-0.43228
15	-0.13591	0.06574	-2.06752
16	0.39761	0.07619	5.21877
17	-0.57718	0.05767	-10.009
18	-0.28696	0.06617	-4.33682
19	-0.03931	0.06776	-0.58008
20	0.24745	0.13501	1.83275
21	0.28878	0.07293	3.95998
22	0.0809	0.06671	1.21267
23	-0.03119	0.06097	-0.51145
24	0.10361	0.06023	1.72022
25	-0.27219	0.06927	-3.92958
26	-0.10596	0.06481	-1.63494
27	0.07082	0.06934	1.02139
28	-0.00979	0.06373	-0.15369
29	-0.30083	0.08776	-3.42795
30	-0.20795	0.09362	-2.22111
31	-0.14788	0.07011	-2.10931
32	-0.20758	0.06135	-3.38333
33	0.03676	0.06016	0.61106
34	0.04006	0.05845	0.68532
35	0.04787	0.05727	0.83582
36	0.12967	0.06231	2.08086
37	0.4708	0.07165	6.57134
Estimated Fixed Effects- periods, normalized to sum to 0			
Period Effects	Coefficient	Standard Error	t-ratio
1	-0.09491	0.03437	-2.76151
2	-0.02935	0.031	-0.94669
3	-0.04204	0.02735	-1.53703
4	-0.0416	0.03363	-1.23685
5	0.00319	0.02373	0.13451
6	0.04423	0.02604	1.69843
7	0.07249	0.02587	2.80191
8	0.08349	0.03837	2.17613

The following tables (from Table 38 onwards) report the results of similar analyses to the above, the only difference is that cows have been included as a variable to see whether this improves the results or not. Table 38 shows the results of OLS without group dummy variables but with cows included as a herd size variable. With cows, strictly speaking the results show that it is a fixed effect model because the Hausman value obtained is 59.3 which is well outside the critical Hausman value of about 50. The results with cows are the next and this is close to accepting the random effects model. In a nutshell, the inclusion of cows yielded slightly better results, as already stated, with a R^2 of 0.9227 against 0.915 for no cows, likelihood statistics of 177 compared with 165 and the sum of elasticities is higher.

Table 38: OLS without group dummy variables: OLS regression – with cows

LHS=Q01MD Mean	-0.4066192E-14
Standard deviation	0.4356070
WTS=none Number of observations	256
Model size Parameters	37
Degrees of freedom	219
Residuals Sum of squares	13.52686
Standard error of e	.2485286
Fit R-squared	0.7204451
Adjusted R-squared	0.6744909
Model test F[36, 219] (prob)	15.68 (.0000)
Diagnostic Log likelihood	13.13576
Restricted(b=0)	-150.0075
Chi-sq [36] (prob)	326.29 (.0000)
Info criter. LogAmemiya Prd. Crt.	-2.649399
Akaike Info. Criter.	-2.651438

Including cows among the variables (see Table 32) gives a markedly different set of results as opposed to not including it (see Table 28). Again, the constant term in the regression, -.0196 in Table 39, is the model intercept and the individual intercepts in Table 32 should be used to adjust the model constant. With the inclusion of cows, Farm 1 now appears less efficient and Farm 36, 13, 6, and 35 are the most efficient, reported in descending order. The test statistics of the model reveal that group effects only account for 78% of the explanatory power and X-variables only account for 72% as indicated by the R^2. The combined explanatory power of the X-variables and group effects work much better as it accounts for some 91.4%.

Table 39: Panel data analysis of output at 2001 constant and mean-differenced [ONE way] Unconditional ANOVA

Source	Variation	Degrees of Freedom	Mean Square		
Between	37.5116	36.	1.04199		
Residual	10.8756	219.	.496602E-01		
Total	48.3871	255.	.189753		
Variable	**Coefficient**	**Standard Error**	**t-ratio**	**P[|T|>t]**	**Mean of X**
LAND	.08009915	.07158423	1.119	.2644	-.386496D-14
LABOUR	.19568750**	.06150852	3.181	.0017	.543315D-14
FEED	.16242578**	.04807963	3.378	.0009	-.682093D-14
VET	.06768329	.02243748	3.017	.0029	-.208167D-15
MILKMACHINERY	.07002960	.02465251	2.841	.0049	-.596745D-14
OTHERMACHINERY	.04556857	.03133608	1.454	.1473	-.875688D-14
$LAND^2$	-.38289221	.20335581	-1.883	.0610	.13144942
$LABOUR^2$	.02270179	.08193244	.277	.7820	.18348085
$FEED^2$	.01784055	.01999699	.892	.3733	.39565140
VET^2	-.03906800	.01673029	-2.335	.0204	.93856974
$MILKMACHINERY^2$	-.01287804	.01863020	-.691	.4901	.90627453
$OTHERMACHINERY^2$	.03196483	.02105532	1.518	.1304	.64171949
LANDLABOUR	-.39417598	.24431796	-1.613	.1081	.08708436
LANDFEED	-.11357920	.16225241	-.700	.4847	.07937033
LANDVET	.01145420	.08087323	.142	.8875	.13509150
LANDxMILKMACHINERY	.29251831**	.07825161	3.738	.0002	.14284474
LANDxOTHER	.02375017	.09887740	.240	.8104	.13006496
LABOURxFEED	.01486130	.13232405	.112	.9107	.11063531
LABOURVET	.01828653	.07348726	.249	.8037	.12776659
LABOURxMILKMACHINERY	-.03241585	.07872859	-.412	.6809	.13434051
LABOURxOTHERMACHINERY	.12827204**	.11694137	1.097	.2739	.10786903
FEEDxVET	.07088036	.05132965	1.381	.1687	.17837069
FEEDxMILKMACHINERY	-.05734697	.04594663	-1.248	.2133	.17409271
FEEDxOTHERMACHINERY	.03203350	.07535451	.425	.6712	.13588410
VETxMILKMACHINERY	-.00528091	.02552041	-.207	.8363	.40810410
VETOTHER	.00663518	.03598047	.184	.8539	.40612140
MILKxOTHERMACHINERY	-.01013240	.03693655	-.274	.7841	.39481209
DRYCOWS	.00284762	.00221307	1.287	.1995	18.2586571
LCOWS	.42807606	.09731803	4.399	.0000	-.656072D-14
$COWS^2$	-.04029322	.27376508	-.147	.8831	.09548948
COWSxLAND	.16267659	.30169950	.539	.5903	.05502525
COWSxLABOUR	.15452932	.31368746	.493	.6228	.07971622
COWSxFEED	.17494319	.22421908	.780	.4361	.08537859
COWSxVET	-.07039919	.10160959	-.693	.4891	.05187837
COWSxMILKMACHINERY	-.21189865	.12371275	-1.713	.0882	.07336205
COWSxOTHERMACHINERY	.04326919	.12351352	.350	.7264	.02867294
Constant	-.01955524	.05316543	-.368	.7134	

Table 40 shows the least squares with group dummy variables. Although the fact that the adjusted R^2 is high (0.88) which, at face value appears to mean that 88% of variation is explained, limited information can be gleaned from these results. It is worth mentioning that the coefficients are quite low and add to much less than 1. The high Chi^2 [72] of = 628.24 can also be deceptive as the least squares models seeks to maximise this statistic. Thus a high Chi-sq is normally desired. Table 40 is mainly included to illustrate how laborious it was to arrive at the models that worked. It also buttresses the point that the correct model is data specific and no *a prior* assumption can be made, with a high degree of certainty, as to which model is the most suited.

Table 40: Least squares with group dummy variables

				R-squared = 0.88	
				Wald Chi-squared [72] = 628.24	
Variable	**Coefficient**	**Standard Error**	**t-ratio**	**P[|T|>t]**	**Mean of X**
LANDMD	0.040892	0.088664	0.461	0.6451	-.386496D-14
LABOURMD	0.203321	0.049402	4.116	0.0001	.543315D-14
FEEDMD	0.098538	0.033941	2.903	0.0041	-.682093D-14
VETMD	0.040852	0.01517	2.693	0.0076	-.208167D-15
MILKMACHINERYMD	0.0101	0.019621	0.515	0.6073	-.596745D-14
OTHERMACHINERYMD	0.014623	0.022416	0.652	0.5149	-.875688D-14
LANDMD^2	0.00367	0.178695	0.021	0.9836	0.131449
LABOURMD^2	0.000871	0.055553	0.016	0.9875	0.183481
FEEDMD^2	0.011084	0.014913	0.743	0.4581	0.395651
VETMD^2	-0.0325	0.011322	-2.871	0.0045	0.93857
MILKMACHINERYMD^2	-0.02161	0.015764	-1.371	0.1718	0.906275
$\text{OTHERMACHINERYMD}^2$	0.011804	0.01505	0.784	0.4337	0.641719
LANDLABOUR	-0.19724	0.165899	-1.189	0.2358	0.087084
LANDFEED	-0.10377	0.110494	-0.939	0.3487	0.07937
LANDVET	0.06219	0.055658	1.117	0.2651	0.135092
LANDMILKMACHINERY	0.114054	0.071605	1.593	0.1126	0.142845
LANDOTHER	0.086076	0.087537	0.983	0.3265	0.130065
LABOURFEED	0.055984	0.089527	0.625	0.5324	0.110635
LABOURVET	0.017372	0.049599	0.35	0.7265	0.127767
LABOURMILKMACHINERY	0.035215	0.059373	0.593	0.5537	0.134341
LABOUROTHER	-0.01075	0.080523	-0.134	0.8939	0.107869
FEEDVET	0.058797	0.034673	1.696	0.0913	0.178371
FEEDMILKMACHINERY	-0.11458	0.031655	-3.62	0.0004	0.174093
FEEDOTHER	0.061644	0.050609	1.218	0.2245	0.135884
VETMILKMACHINERY	0.031611	0.017397	1.817	0.0706	0.408104
VETOTHER	-0.02547	0.024686	-1.032	0.3033	0.406121
MILKOTHERMACHINERY	-0.02025	0.029076	-0.696	0.4869	0.394812
DRYCOWS	0.002304	0.001443	1.597	0.1118	18.25866
LCOWSMD	0.21723	0.095312	2.279	0.0236	-.656072D-14
COWS^2	0.659	0.227127	2.901	0.0041	0.095489
COWSLAND	0.040136	0.255604	0.157	0.8754	0.055025
COWSLABOUR	-0.24771	0.223024	-1.111	0.2679	0.079716
COWSFEED	0.009012	0.153764	0.059	0.9533	0.085379
COWSVET	-0.0379	0.071726	-0.528	0.5977	0.051878
COWSMILKMACHINERY	-0.05173	0.108653	-0.476	0.6345	0.073362
COWSOTHER	-0.04531	0.094903	-0.477	0.6335	0.028673

Little more can be gained by changing the specification of the panel production function models, so the logical progression is to attempt to fit frontiers, which will generate more information on the individual farms.

5.6 Stochastic frontier models

5.6.1 Some theoretical background

As a more comprehensive coverage of the theory on stochastic frontiers is given in Chapter 2, it would suffice to give a brief recap here. The measurement of firm level technical efficiency has become commonplace with the development of frontier production functions. The approach can be deterministic, where all deviations from the frontier are attributed to inefficiency, or stochastic, where it is possible to discriminate between random errors and differences in inefficiency. The stochastic frontier model was originally proposed by Aigner, Lovell and Schmidt (1977). Fried, Lovell and Schmidt (1993) render a comprehensive survey of methods and applications, that were extended to include the characteristics of the firm that explain the inefficiency, following the work of Battese and Coelli (1995). This approach allows the use of panel data and is estimated such that the technical inefficiency effects are specified as factors that interact with the input variables of the frontier function. Whereas ordinary least squares (OLS) estimation takes the average line of best fit through the observations (a mean response function) and tacitly assumes that all the firms are efficient, this can be misleading if there are considerable differences in efficiency levels. Tests show whether a production frontier is the appropriate model, and efficiency levels are estimated for each farm, in each year.

Thus, the frontier model identifies the firms that represent best practice, and the inefficiencies are explained using the method of maximum likelihood to estimate the unknown parameters, with the stochastic frontier and the inefficiency effects estimated simultaneously. The theory is described in full in Coelli (1995), Coelli, Rao and Battese (1998) and many applications are discussed in Bravo-Ureta and Pinheiro (1993). The estimating equation is

$$\begin{aligned} y_{it} &= f(x_{j,it}, t, \beta) + \varepsilon_{it} \quad \text{where } \varepsilon_i = V_{it} - U_{it} \\ \text{with} \quad U_{it} &\sim |N(\mu_{it}, \sigma_U^2)| \quad \text{and} \quad V_{it} \sim N(0, \sigma_V^2) \end{aligned} \qquad \textbf{(5.18)}$$

where f(.) is a suitable functional form, y_{it} is the output of farm *i* at time t, $x_{j,\,it}$ is the corresponding level of input *j* and β is a vector of parameters to be estimated. The V_{it}*'s* are independently and identically distributed random error terms and uncorrelated with the regressors, and the U_{it}'s are non-negative random variables associated with the technical inefficiency of the farm. If the residuals are negatively skewed, the maximum likelihood estimator for the stochastic frontier production function model is simply OLS (Waldman, 1992). In this case, either the model is mis-specified or the data are not consistent with the functional form. In the second part of the model, this inefficiency term, U_{it}, is made an explicit function of *k* explanatory variables, $z_{k,it}$, that represent the characteristics of the farms. The U_{it} are independently (but not identically) distributed as non-negative truncations of the normal distribution of the form

$$U_{it} \sim N\left[\delta_0 + \sum_{k=1}^{M} \delta_k z_{k,it}, \sigma^2\right] \tag{5.19}$$

The technical efficiency of an individual farm is defined in terms of the ratio of the observed output to the corresponding frontier output, conditional on the levels of inputs used by that farm. Thus, the technical efficiency of farm *i* at time t in the context of the stochastic frontier production function can be expressed in terms of the errors as

$$TE_{it} = E[\exp(-U_{it}) | (V_{it} - U_{it})] \tag{5.20}$$

which is the expectation of the exponentiated technical inefficiencies, conditional on the error, ε_{it}. Since U_{it} is a non-negative random variable these technical efficiencies fall between zero and unity, where unity indicates that this farm is technically efficient. Two frontier models were estimated, the CD and the TL, defined as

$$y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j x_{jit} + V_{it} - U_{it} \tag{5.21}$$

and

$$y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j x_{jit} + \sum_{j=1}^{J} \sum_{k=1}^{J} \beta_{jk} x_{jit} x_{kit} + V_{it} - U_{it} \tag{5.22}$$

respectively. All the variables are in logarithms, except the time trend and the percentage of the herd that is dry (not producing milk), and in Equation 5.22 all are mean differenced to allow direct estimation of the elasticities, evaluated here at the mean.

5.6.2 Results

The first model tested was the CD, Equation 5.21, in which the variables are linear in logarithms. However, is a remarkably restrictive functional form as it assumes that the elasticity of substitution between any pair of variables is unity. As these constraints are unlikely to be accepted in models fitted to an adequate number of observations other functional forms are also modelled and tests performed to determine which model best represents the data. The unconstrained functional form most commonly used is the translog (TL), which is a flexible functional form (Equation 5.22). This means that it can adequately represent any unknown underlying true production function and thus squared and cross product terms are included. In this way the elasticities of substitution can be estimated rather than imposed and can be different for each pair of inputs. Before the TL function is estimated, the data are mean centred to avoid complex calculations to retrieve the elasticities.

Model selection is based on a series of hypothesis tests using generalised likelihood ratio (LR) tests, with the results of these tests reported in Table 41. These tests include: (1) the functional form test, of the adequacy of the CD relative to the TL; (2) the frontier specification relative to the mean response function jointly with the separation of the inefficiency terms from the frontier variables and (3) whether the inefficiency terms should be separated or included in the frontier production function.

In all three models the TL is a better representation of the data than the CD. There are two tests to determine whether the model is a frontier or a mean response function. The gamma coefficient is significantly different from zero for Models I and III at the 95% level but this is rejected for Model II and it is only significant at the 90% level. In the more robust log likelihood ratio test Models I and III are frontiers but Model II is a mean response function. Despite this ambiguity, the technical efficiency terms can be calculated although as noted in the discussion section, these are not strictly comparable with the other two models. Finally, for both Models I and III, the inefficiency terms are separate from the production function. This test is not applicable to Model II, as there are no such terms.

Table 41: Hypothesis for cows excluded (Model I), cows included without inefficiencies (Model II) and cows included with inefficiencies (Model III)

Model I Likelihood statistic = 21.6 – Regressors 31						
(1) Functional Form Test	Log-Likelihoods[17]		LLR Test	DoF	χ^2_{15} Critical value at 5%	Outcome
Parameter Restrictions	H_0: CD	H_1: translog	Statistic			
H_0: All $\beta_{jk} = 0$	-10.162	23.410	33.572	22	33.91	Reject H_0 - CD is inadequate
(2) Frontier Tests			LLR test		Parameter Restrictions: H_0: $\gamma = \delta_i = 0$	
	Gamma	t stat	Statistic	DoF	Critical Value	Outcome
	0.5081	3.7915	58.236	6	12.59	Reject H_0 - frontier not OLS
(3) Inefficiency Model	H_0: δ=0	H_1: $\delta \neq 0$				Reject H_0 – the δ_i do explain the inefficiencies
	-3.247	21.626	49.746	4	9.488	
Model II Likelihood statistic = 52.9 – Regressors 35						
(1) Functional Form Test	Log-Likelihoods		LLR Test	DoF	χ^2_{15} Critical value at 5%	Outcome
Parameter Restrictions	H_0: CD	H_1: translog	Statistic			
H_0: All $\beta_{jk} = 0$	16.833	-22.140	77.948	28	43.77	Reject H_0 - CD is inadequate
(2) Frontier Tests			LLR test		Parameter Restrictions: H_0: $\gamma = \delta_i = 0$	
	Gamma	t stat	Statistic	DoF	Critical Value	Outcome
	0.5429	1.683	0.374	1	3.84	Accept H_0 – OLS not frontier
Model III Likelihood statistic = 65.3 – Regressors 26						
(1) Functional Form Test	Log-Likelihoods		LLR Test	DoF	χ^2_{15} Critical value at 5%	Outcome
Parameter Restrictions	H_0: CD	H_1: translog	Statistic			
H_0: All $\beta_{jk} = 0$	31.557	64.995	66.862	16	26.3	Reject H_0 - CD is inadequate
(2) Frontier Tests			LLR test		Parameter Restrictions: H_0: $\gamma = \delta_i = 0$	
	Gamma	t stat	Statistic	DoF	Critical Value	Outcome
	0.3865	1.9897	20.10	5	11.07	Reject H_0 – frontier not OLS
(3) Inefficiency Model	H_0: δ=0	H_1: $\delta \neq 0$				Reject H_0 – the δ_i belong in the frontier
	64.250	50.446	27.608	4	9.488	

Table 42 reports the maximum likelihood estimates for the three selected models. This includes the TL frontier production function and the inefficiency terms, which will be discussed in conjunction with the inefficiencies themselves. The output elasticities are the coefficients of the direct terms (listed at the top). For the net outputs approach in Model I, the direct terms are all significant at the 5% confidence level or better, except for land, which is barely significant only at the 10% level. If

[17] Note: The likelihood-ratio (LLR) test statistic, $\lambda = -2\{\log[\text{Likelihood } (H_0)] - \log[\text{Likelihood } (H_1)]\}$ is distributed approximately χ^2_v where $_v$ is the number of parameters assumed to be zero in H_0. Where the null hypodissertation involves the parameter γ, which as a ratio of two variances is necessarily positive, the test statistic has a mixed chi-squared distribution. The critical values are found in Kodde and Palm (1986).

herd size is not included in the inefficiency model, the elasticity for land increases to 0.203 and its t statistic increases to 3.75. Thus, it seems fair to say that it is the double counting problem that is responsible for this one weak result.

Table 42: Stochastic Frontier Maximum Likelihood Estimates

	Model I No cows		Model II Cows, no inefficiencies		Model III, both, with cows	
Regressor	coefficient	t stat	coefficient	t stat	coefficient	t stat
Constant	0.3593	4.1895	0.2011	2.5593	0.3027	1.9480
Cows			0.3913	3.7710	0.0154	0.0733
Land	0.0765	1.2931	0.0638	0.9392	0.1255	2.3567
Labour	0.2092*	3.6741	0.2102	3.4880	0.1072	2.2310
Feed	0.1496	3.6288	0.1702	3.7319	0.1293	3.8725
Veterinary_{t-1}	0.0694	3.2546	0.0705	3.3842	0.0530	3.0533
Milk Machinery	0.0597	2.5874	0.0714	3.0756	0.0761	3.8374
Tractors	0.0605	2.1037	0.0472	1.6070	0.0301	1.3040
Land^2	-0.1281	-0.7160	-0.0379	-0.1489		
Cows^2			-0.4008	-2.0718	-0.1928	-1.2526
Labour^2	0.0387	0.5862	0.0236	0.3151		
Feed^2	0.0358	2.2152	0.0113	0.5935	0.0133	1.0536
Veterinary^2	-0.0324	-1.9713	-0.0379	-2.4443	-0.0277	-2.5646
Milk Machinery^2	-0.0241	-1.4154	-0.0143	-0.8309		
Tractors^2	0.0333	1.6633	0.0365	1.7734		
Cows*Land			-0.3883	-1.7199	-0.2816	-1.6137
Cows*Labour			-0.1562	-1.0178	-0.3122	-2.7650
Cows*Feed			0.0026	0.0350		
Cows*Veterinary			0.2983	4.1563	0.2240	4.4018
Cows*Milk Mach			0.0331	0.3595	0.0914	1.4516
Cows*Tractors			-0.0176	-0.1391		
Land*Labour	-0.3683	-1.8507	0.0130	0.1915	-0.0202	-0.4342
Land*Feed	-0.1156	-0.8133	-0.0267	-0.3684		
Land*Veterinary	-0.0361	-0.5236	0.1557	1.4128	0.0766	0.9770
Land*Milk Mach	0.3354	4.7040	0.0794	1.6806	0.0628	1.7761
Land*Tractors	-0.0137	-0.1584	-0.0581	-1.3724	-0.0300	-0.9319
Labour*Feed	0.1069	1.0730	0.0308	0.4398	0.0292	0.5423
Labour*Veterinary	0.0252	0.3935	-0.0016	-0.0638		
Labour*Milk Mach	-0.0619	-0.9643	-0.0028	-0.0784		
Labour*Tractors	0.1080	1.0751	-0.0134	-0.3863		
Feed*Veterinary	0.0686	1.4335	0.1875	0.6746	0.2874	1.3004
Feed*Milk Mach	-0.1054	-2.5824	0.1335	0.4625	0.2403	1.3498
Feed*Tractors	0.0372	0.5314	0.2530	1.1598	0.1763	1.2999
Veter'y*Milk Mach	-0.0261	-1.0250	-0.0941	-0.9013		
Veterinary*Tractors	0.0246	0.7616	-0.2184	-1.8769	-0.2030	-2.7644
Milk Mach*Tractors	0.0015	0.0458	0.0761	0.6078		
Inefficiency effects						
Constant					0.7611	2.3525
Year	0.0004	6.7884				
Capital Investment	-0.0063	-1.3312			-0.0057	-1.6966
% Dry Cows	0.0109	3.9589			0.0095	3.9910
Herd Size	-0.0024	-4.3792			-0.0022	-3.1698
Likelihood statistic	21.6		52.9		65.3	
gamma	0.5200	3.4583	0.5429	1.6831	0.3865	1.9897

In addition, four squared terms and four cross products are significant. The negative signs on the squared terms indicate decreasing returns to veterinary services and milking machinery, whereas there is evidence of increasing returns to tractors and feed. The elasticities on the direct terms sum to only 0.63, which raises the possibility that the farms are too big. In fact, farm size has been increasing substantially for some time in Midlands, due to the small margins on dairy production.

Four variables are included to explain the farm level efficiencies. Firstly, the positive sign on the year variable indicates that time increases the inefficiency levels, although the coefficient is very small, at 0.04% per year. Not surprisingly, capital investment has a positive impact on these farms, while the size of the herd is also contributing to higher levels of efficiency, which is contrary to the dubious returns to scale result reported above. Last, the proportion of the herd that is dry lowers efficiency, which is obvious.

The gross output approach in Model II includes cows fully in the TL function. The direct terms now sum to 1.025, which supports the more sensible proposition of slightly increasing returns to scale. All the elasticities are significant, except that for land, which is rendered totally insignificant by the full inclusion of cows and the double counting that implies. Table 42 showed that the t test on the value of gamma indicate that this model was a frontier when no inefficiency terms were included, but the superior log likelihood ratio test indicated that it is a mean response function. The problem is that with the double counting of inputs, the function fits so well that it is reaching the point where there is nothing left that can be called inefficiencies.

Finally, in Model III some of the insignificant non-linear and cross product terms were omitted and the model re-estimated using the inefficiency variables in Model I. The results are similar to those for Model II except that land is now significant rather than cows, which is wiped out by having herd size as an inefficiency variable. However, the number of cows is important in explaining inefficiency, as well as the proportion of dry cows and capital investment, as in Model I. If herd size is left out of the inefficiency the only result that is changed significantly is that the elasticity of cows increases to 0.488 with a t statistic of 7.02, but land retains its elasticity and significance.

Conducting likelihood ratio tests, using the likelihood statistics in the penultimate row, shows that Model II is preferred to Model I, but Model III is preferred to both. Indeed, it should be, as dropping eleven insignificant squares and cross products allows three significant inefficiency terms to be included, while still reducing the number of terms by eight. Thus, it wins the unfair comparison as its likelihood statistic actually increases despite having fewer terms. The conclusion to the debate on including cows in the frontier can be resolved in this way. The herd size does not belong in the frontier, but it does an excellent job of improving the model when it is used in the inefficiency terms to establish that there are increasing returns to scale.

The next set of results relates to the average farm-level efficiencies that are reported by year in Table 43 and depicted in Figure 17. The year coefficient in the inefficiency model for Model I indicates a negative time trend, however it is now clear why this is so, as there is not a monotonic increase in efficiencies although the overall trend is positive. The mean efficiencies have risen except in 2002 and 2003, but the dispersion is greater, falling for the first four years and then rising for the second four. For example, the maximum value in 2000 was 90.4% efficiency but this rose to 96.9%. This best practice farm has only scope for a 3.1% possible improvement by the end of the period.

Table 43: Farm level efficiency levels

	Model I				**Model II**				**Model III**			
Year	Mean	St. dev	Min	Max	Mean	St. dev	Min	Max	Mean	St. dev	Min	Max
2000	0.685	0.123	0.487	0.904	0.857	0.055	0.704	0.959	0.702	0.113	0.536	0.925
2001	0.707	0.113	0.471	0.897	0.868	0.044	0.751	0.933	0.725	0.101	0.545	0.929
2002	0.705	0.117	0.480	0.942	0.857	0.049	0.727	0.939	0.734	0.108	0.532	0.961
2003	0.704	0.105	0.467	0.952	0.858	0.051	0.708	0.918	0.736	0.093	0.547	0.966
2004	0.723	0.131	0.463	0.956	0.838	0.070	0.609	0.918	0.759	0.116	0.512	0.971
2005	0.731	0.144	0.435	0.962	0.839	0.067	0.670	0.950	0.768	0.133	0.509	0.976
2006	0.744	0.141	0.504	0.969	0.854	0.060	0.649	0.934	0.778	0.127	0.532	0.980
2007	0.770	0.147	0.497	0.969	0.854	0.055	0.731	0.937	0.807	0.131	0.550	0.982
Efficiency by farm size – measured by herd size												
	Mean		St. dev		Mean		St. dev		Mean		St. dev	
Small	0.6973		0.1144		0.8599		0.0494		0.7209		0.1049	
Medium	0.7193		0.1252		0.8464		0.0629		0.7575		0.1189	
Large	0.7454		0.1412		0.8508		0.0602		0.7761		0.1229	
Analysis of variance												
	0.00058				0.0000474				0.000789*			

In Model II, the mean efficiencies are higher, which is not surprising as the frontier function variables account for most of the performance and there is less dispersion across the farms. The lower end of the distribution is more efficient in this model, ranging from 70.4% in 2000 to 73.1% by the end of the period. Finally, the average efficiency levels in Model III increase in each year, with the improvement close to 10%.

Figure 17 is a graphical representation of the three models that have been presented. The efficiency scores for the farms do not vary much over the years. However, it is interesting to note that Model I and III exhibit slightly increasing efficiencies over the years for the farms while Model II shows somewhat constant efficiencies with periods of slight declines in the farms' efficiencies.

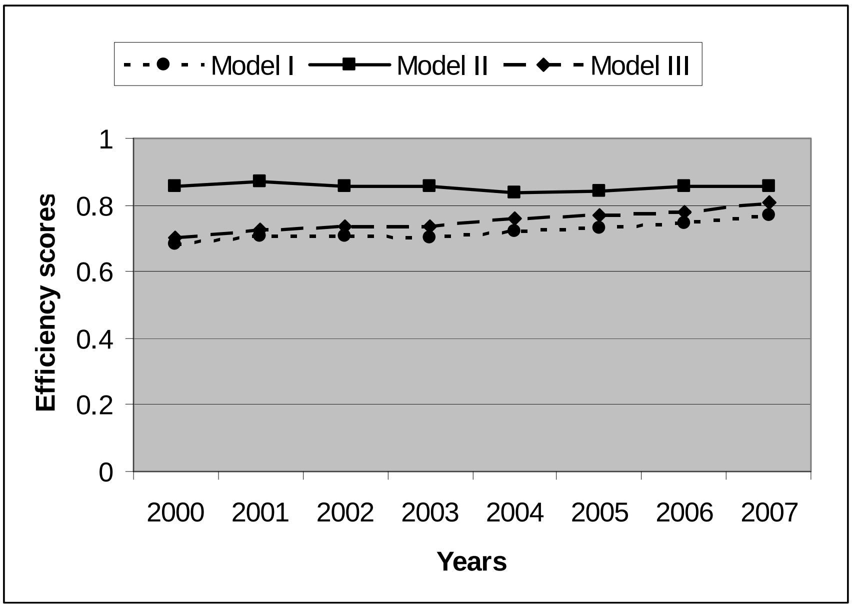


Figure 12: Mean annual farm level efficiency, 2000-2007

Finally, the lower section of Table 43 examines whether the size of farm, measured by herd size, has an impact on efficiency. The farms were ranked by size and the sample divided into three groups. The means and variances of their associated efficiencies were then computed. The results corroborate the increasing returns result in the inefficiency models, showing that in Models I and III, on average, the large farms are more efficient than the medium ones, and these are more efficient than the small ones. These two models include herd size in the inefficiency effects and pick up this effect. Model II does not have inefficiency variables and so shows no scale effect.

5.7 Summary on production and efficiency of the dairy farms

This section provides a summary on productivity, efficiency, technological change and returns to scale of the dairy farms in the KwaZulu-Natal Midlands. It is worth noting that productivity growth, as postulated in the literature, is as a result of changes (increases) in efficiency, technological change and returns to scale. Thus it suffices to briefly recap and highlight the salient results that can be gleaned from the analyses performed in this chapter.

The most striking feature of this chapter is the revelation that these data are sufficient to support quite complex econometric estimates. Despite the foregoing assertion it is proper to concede that although the results are simple and straightforward, they can be construed as ambiguous to a certain extent.

The topical issue of technical change deserves a brief discussion here. The time trends were included in the production function in the models presented earlier in this chapter and the time effect is usually positive. This is true in the one- and two-way error components models and in the frontier results estimated using Stata. However, the frontier models are different from the one- and two-way error models. Time is included in the inefficiency Model 1 as an inefficiency-explaining variable (z) and it had a positive effect meaning it increases inefficiency. Care has to be taken in explaining and understanding the inefficiency results as this may be counter intuitive to some. Unlike in the efficiency model, a positive effect in the inefficiency model means that the particular variable increases inefficiency. The overall deduction here is that, on balance, technical change is positive even though this cannot be unequivocally be stated.

5.7.1 Efficiency and size

As was pointed out earlier, the trend in South African dairy production is towards bigger herds. Following the example of Bravo-Ureta and Rieger (1991), an analysis of variance (ANOVA) and the Kruskal-Wallis test were conducted in order to determine the effect of size upon the efficiency indices (see Table 43). Size was measured as the number of dairy cows (herd size) as this variable proved to be a better measure of size than the amount of milk produced. A farm with a herd size less than the 33rd percentile is considered small. A farm having herd size between the 33rd percentile and the 66th is considered medium sized. Finally the farms above the 66th percentile are considered large. The ANOVA results shown in Table 43 show statistical significance for differences between small, middle sized and large farms in technical efficiency. The other results give no evidence for differences in technical efficiency due to differences in size, except for Model II where there were significant differences between the farm sizes with the larger farms performing marginally better.

5.7.2 Share parameters for inputs in the stochastic dairy production function

There is little difference between the estimated coefficients in Models 1, 2 and 3 in Table 42, particularly between Model 1 and 2. Coefficient values show constant returns to scale (more or less), implying no scale effects in the size of operation so that farm size and output are proportional (at least for the estimated results presented here). In more general terms, productivity change will depend on improvements in technology and efficiency, and not necessarily on larger or smaller farm size.[18]

All input variables are measured in log form, so that estimated coefficient values represent 'share parameters' or elasticities. Thus, using Model II as an example, a 1 per cent increase in the number of livestock capital (herd size) results in an estimated increase in dairy output of 0.39 percent (for Model II). Out of all input variables cows has the highest share coefficient (0.39), followed by labour (0.21), feed (0.15) and land (0.08). Land, though significant, account for only 0.08, implying that for a 1 percent increase in land size results in an estimated 0.08 percent increase in output. This finding, however, needs to be taken in the context of the model. Model II includes both land and cows and this could be double-counting as discussed earlier in the conceptual framework section. If the double-counting argument is accepted then the results are not surprising as cows may be wiping out land. In Model I labour records the highest elasticity (0.21), followed by feed with 0.15, then land (0.077), veterinary expenditure – lagged one period (0.069), other machinery (0.0605) and milk machinery (0.0597). This indicates approximately constant returns to scale (0.9842), including the constant term.

5.7.3 The effects of technology and farm specific variables on economic efficiency

A number of technology and farm-specific features are considered in the technical inefficiency model. They are farm size (measured in herd size), percentage of dry cows, and capital investment. All other variables in the technology dataset tested as highly insignificant. Farm size in terms of the area of the farm utilized by the milking herd tested as insignificant. The number of cows and percentage dry cows at peak season tested as significant (albeit at the 10 per cent level), but its coefficient value is very small, suggesting little change in efficiency from an increase in this variable.

Although no similar study has been done in the dairy industry in South Africa, a brief note on the findings of other researchers elsewhere will suffice in putting the discussion into perspective. Jaforullah and Devlin (1996) also find no relationship between farm size and efficiency. Hallam and Machado (1996) find that larger farm size per cow increases efficiency, but do so using a two-step procedure (OLS estimates of farm characteristics on efficiency rankings) with potential bias in the

[18]Estimating a stochastic production frontier, without a technical inefficiency model, Jaforullah and Devlin (1996) show that despite an industry trend toward larger dairy farm size in New Zealand, that there is no evidence that larger farms are more efficient and that the dairy farm sector is characterized by constant returns to scale. Loyland and Ringstad (2001) find unexploited scale-economies in Norwegian dairy production, but attribute these to agricultural policy, with a comprehensive system of public economic support and regulation.

results. Based on a survey questionnaire (of dairy firms, scientists and other experts), Caraveli and Traill (1998) find some support for the claim that new technologies imply that average costs of production fall more for larger farms.

5.8 Concluding remarks

This section of the chapter uses stochastic frontier and inefficiency models to test the efficiency of dairy production in Midlands of KwaZulu-Natal. The estimation of the stochastic production frontier and the associated technical efficiency model were done to determine the importance of inputs in dairy production and the farm-specific characteristics that explain differences in efficiency across dairy farms in KZN Midlands. The data covers a panel of 37 dairy farms for the 1999 to 2007 period. Tests show that the data is adequate to allow complex analyses and reveal that the CD stochastic production frontiers, with variables to explain the inefficiencies are an appropriate representation of the sample.

The stochastic frontier results indicate that output can be explained by land, cows (herd size), labour (labour wage as a quality of labour variable), milking machinery and other machinery (cost of running these machinery categories) and that efficiency can be affected by labour quality, percentage of dry cows in the herd, herd size, capital investment and passage of time. Efficiency is also dependent on farm size and/or herd size, so returns to scale are further investigated using data envelopment analysis to elucidate which quartile of farms is more scale efficient than the rest.

Although the dataset used is good enough to produce reasonable results without pooling, it must be conceded that most researchers in applied economics would consider the possibility of improving the estimates by pooling the samples. Pooling tests performed in this chapter show that in this situation, given the small sample that notwithstanding that pooling is permissible it may not be helpful.

Following is a section reporting results from the DEA analyses. As has already been indicated earlier in this study, the results of an efficiency study can be sensitive to the method selected to estimate the efficiency scores. The two most popular techniques used to measure farm efficiency are the DEA (Charnes *et al*., 1978) and the SFA (Aigner *et al*.,1977; Meeusen and Van den Broeck, 1977). The former uses mathematical linear programming methods, whereas the latter uses econometric methods. The choice of which method to use has to be decided in every case because it is not always obvious.

The quality of the data, the appropriateness of various functional forms, and the possibility of making behavioural assumptions will heavily influence the relative appropriateness of DEA and SFA. For example, the DEA approach, compared to the SFA does not require any specific functional form to be selected, neither are any behavioural assumptions needed as long as allocative efficiency is not considered. However, DEA is a deterministic approach, meaning that it does not account for noise in the data. All deviations from the frontier will thus be accounted for as inefficiencies. Therefore the DEA efficiency scores are likely to be sensitive to measurements errors and random errors. Conversely, the SFA accounts for random errors and has the advantage of making inference possible (Coelli *et al*., 2002). However, SFA is sensitive to the choice of functional form. Obviously, choosing between parametric and nonparametric methods is a delicate matter and some studies comparing the results of two approaches have been done.

There is a two-fold aim for the next chapter. First, it is to compare the relative appropriateness of DEA and SFA in estimating efficiency scores in dairy production. Second, it is to use the results from this analysis to establish measures of efficiency of dairy farms in the KZN Midlands, and how the efficiency measures are influenced by farm size. Particularly, the DEA model gives a different view of returns to scale, as it separates technical and scale efficiency in the variable returns to scale model. Considering the changing structure and market situation of these farms, studies of the economic input efficiency is of high importance to understand the challenges facing the dairy farmers. As the trend in the South African dairy farms seems to be towards bigger herds it will also be interesting to investigate the relationship between efficiency and farm size. This study would give insight into the nature of the problems facing the dairy farms in their quest to become more efficient.

Chapter 6: The DEA approach to efficiency measurement

6.1 Introduction

In the previous chapter efficiency results were generated using the stochastic frontier approach and the CD and TL production functions, and random and fixed effects were reported and discussed. Given that there are two broad approaches to efficiency studies, namely parametric and non-parametric, it becomes useful to look at both in a study of this nature. Consequently, the current chapter will employ the data envelopment analysis (DEA) approach which is both non-parametric and deterministic. The DEA has some advantages or features that the stochastic frontier approach does not possess, thus it is attractive go into the DEA approach to glean some in-depth information that could have been lost or not identified in the previous chapter.

The DEA is a mathematical programming approach for measuring the technical efficiency and economic performance of firms. Charnes *et al.* (1978) are accredited for formally introducing DEA, albeit their work was actually an extension of the works of Shephard (1953, 1970) and Farrell (1957). DEA facilitates the construction of a non-parametric piece-wise frontier over the existing data. Efficiency measures are then derived by exploring the distances between observed input and output combinations and frontier input and output combinations.

The work of Charnes *et al*. (1978) is generally regarded as seminal in terms of the empirical application of DEA. Stokes *et al*. (2007), however, assert that DEA research can be traced seven years earlier to the work of Seitz (1971) and there is no doubt that Charnes *et al.* (1978) work was based on Farrell (1957). Be that as it may, Charnes, Cooper, and Rhodes (CCR) subscribes to the basic notions discussed in Chapter 2. Given that Farrell (1957) is credited with being the catalyst to the development of DEA as it is known, it is worth discussing Farrell's efficiency concept here, albeit briefly.

Figure 18 shows Farrell's basic measure of overall technical efficiency. The inputs are x_1 and x_2 and the frontier of the set $L+(y)$ is the best practice frontier which defines the minimum combinations of inputs required to produce output level y^*. Observations B and C represent efficient producers and thus define the frontier, but the farm represented by observation A uses more of both inputs (x_1 and x_2) to produce the same output (y^*) as farms B and C thus rendering it inefficient. The minimum combination of x_1 and x_2 that farm A could use to output y^* efficiently is represented by the distance OP. It should be observed that the efficient vector is determined using farm A's own factor ratio, that is, the minimum efficient combination of inputs is determined from observed use of inputs by the particular farm. In the illustration the observed or actual combination of inputs used by farm A is OA, thus Farrell's radial measure of the efficiency level of farm A is OP/OA and this will lie between zero and unity.

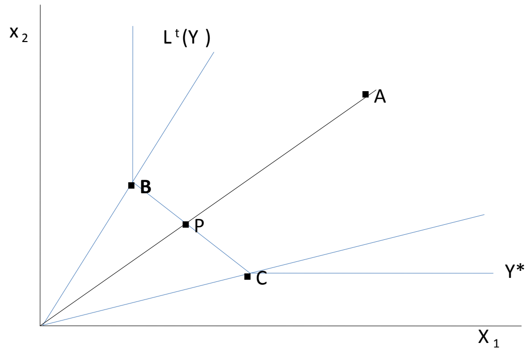


Figure 18: Farrell efficiency measurement

Source: Piesse *et al*. (2000)

Farrell's measure of overall efficiency can be formally depicted as:

$$F(y_i, x_i) = \min[\lambda_i : \lambda_i x_i \in L^+(y)] \quad \textbf{(6.1)}$$

where λ (the minimized parameter) determines the amount by which the observed input combination can be reduced. The efficiency level can be determined by solving the programming problem:

$$\begin{aligned} & F(y_i, x_i) = \min \lambda_i, \\ & subject \quad to \quad zy \geq y_i \\ & zx \leq \lambda_i x_i \\ & z \geq 0 \end{aligned} \quad \textbf{(6.2)}$$

where y is the output matrix, x is the input matrix and z is the vector of farm-specific non-negative intensity parameters, which are used to construct the convex combinations of observed inputs and outputs, and i represents the individual farm. The parameter λ allows for radial scaling of the original observations and their convex sets in order to determine the minimum input usage needed to produce the given level of output (Piesse *et al.*, 2000:138-139; Coelli *et al.*, 1998). The CCR model is run as a linear programme expressed for each Decision Making Unit (DMU or farm in this case) j as:

$$\begin{aligned} &\min \theta_j \\ &\theta_j x_{jm} \geq \sum_{k=1}^{K} x_{km} \lambda_{jk} \text{ for all } m \\ &\sum_{k=1}^{K} y_{ki} \lambda_{jk} \geq y_{ji} \text{ for all } i \\ &\lambda_{jk}, \theta_j \geq 0, \end{aligned} \qquad \textbf{(6.3)}$$

where m indexes inputs so that x_{jm} is the quantity of input m used by DMU j and x_{km} is the amount of input m used by each of the other K DMUs; i indexes outputs so that y_{ji} is the amount of output i produced by DMU j and y_{ki} represents the amount of output i produced by each of the other K DMUs. It is worth drawing the attention of the reader to the fact that the linear programme presented here is solved once for each DMU so that the efficiency is determined for each DMU j relative to each of the other K DMUs in the sample. The basic DEA approach can be broadly either done as constant returns to scale (CRS) or a variable returns to scale (VRS) model.

At the heart of the linear programme is finding an optimal set of weights denoted by λ_{jk} that satisfy the $m \times i$ constraints and give an efficiency score denoted by $0 \leq \theta_j \leq 1$. The scale of the weights gives information about relevant reference groups (known as benchmarks) for each inefficient DMU. In other words, all positive values form the set of potential benchmarks for the inefficient DMU in question. In addition, the largest weight is the most appropriate efficient DMU for the inefficient DMU to benchmark. An important point to note is that it is the DEA model solution that determines the appropriate benchmarks for the inefficient DMU rather than an exogenous source such as an average.

Figure 19 illustrates the frontier for one output and one variable input while holding the other inputs constant. Before discussing the figure, it is worth recapping that the DEA measures efficiency by generating a linear piece-wise surface for the frontier. All points that lie on the frontier are technically efficient combinations of inputs and outputs. Conversely, all points that lie in the interior of the frontier represent inefficient combinations of inputs and outputs. DEA seeks to determine the maximal radial contraction (or expansion) of inputs (or outputs), while still remaining with the feasible input (output) set (Coelli *et al.*, 2005). The projection of observed inputs (or outputs) onto the frontier is done from an input (or output) orientation. Non-orienting projections, however, are also possible with alternative types of DEA models. Unlike regression, which determines a statistical relationship between dependent and independent variables at the conditional mean level, DEA determines optimal solutions for every observation in a data set. Figure 19 depicts the frontier for three types of returns to scale (i.e., the percentage change in output given a one percent change in all input levels). The straight line from the origin represents constant returns to scale (CRS: that is, output increases by x% for a x% increase in all inputs). The segmented line represents variable returns to scale (VRS), with increasing returns to scale (IRS), and non-increasing returns to scale (NIRS).

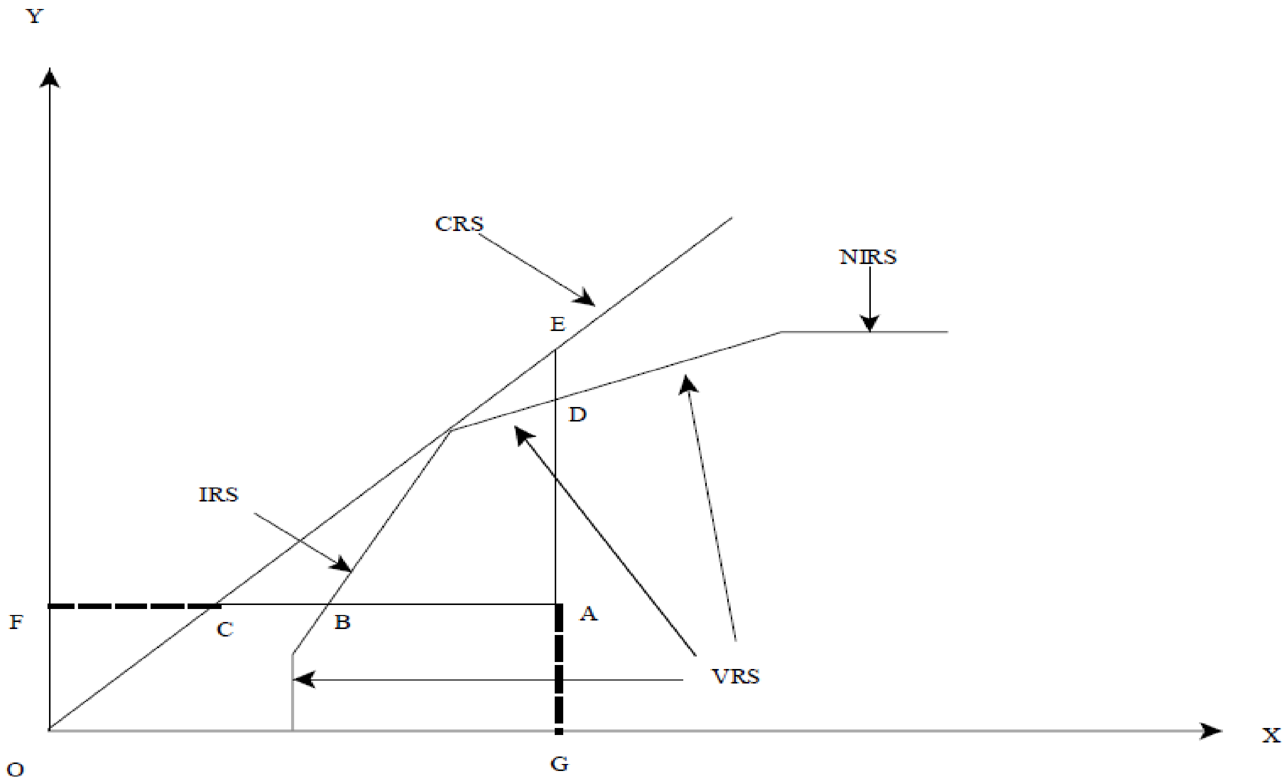


Figure 13: Returns to scale representation of individual observations on DEA

Source: Adapted from Coelli *et al*. (1998:152); Kerstens and Eeckaut (1999)

Conditional on the orientation, DEA facilitates the determination of maximum contractions and expansions of inputs and outputs. From an input orientation and assuming VRS, DEA determines the ratio FB/FA, which indicates the percentage of inputs required to produce an output level corresponding to point f; the CRS reduction is FC/FA. The percentage by which the original input level can be reduced equals unity – FB/FA for the VRS case, and unity – FC/FA for CRS. The output-oriented measure of TE for the VRS case equals the ratio GA/GD, and GA/GE for CRS. The percentage by which outputs could be expanded equals GD/GA, for the VRS case, and GE/GA for CRS. Returns to scale addresses the input and output decisions (orientations) of the DMU (Butler and Li, 2005). Nicholson (1985:247) defined returns to scale as: “In intuitive terms, if a proportionate increase in inputs increases output by the same proportion, the production function exhibits CRS. If the output increases less than proportionately, the function exhibits diminishing returns to scale. And if the output increases more than proportionately, there are increasing returns to scale".

One of the additional features of DEA is that it can determine returns to scale (RTS) more directly, and thus will elucidate valuable information on the RTS in dairying in KwaZulu-Natal. Secondly, because DEA is a non-parametric approach and the production frontier is deterministic, any deviations from the frontier can thus be construed as inefficiency. DEA follows a systems approach in that it takes account of the relationship between all inputs and outputs simultaneously. DEA yields a more consistent measure of efficiency than the more frequently reported partial indicators of farm efficiency. In addition, DEA yields a relative measure of efficiency by identifying those farms that form the frontier and concurrently identifies the farm's peers. DEA also identifies those inputs that are being under-utilised, often referred to as input slacks (Coelli *et al*., 1998) and outputs that are being under-utilised (production at a sub-optimal level where output could be increased without incurring extra input utilisation). Last, but not least, DEA is also advantageous as it leads to the Malmquist index which, in turn, allows one to measure Total Factor Productivity (TFP) and to further decompose the TFP into its different components. The background to and theoretical underpinnings of the concepts of RTS, input and output orientation, input slacks, peers and output will be rendered briefly in the following sections followed by the results of the DEA analysis.

6.2 Estimating returns to scale in DEA models

The beauty of using the DEA is that it facilitates the formal categorization of any single observation according to whether it satisfies constant (CRS), increasing (IRS), or decreasing (DRS) returns to scale by simply identifying the technology yielding the maximal input efficiency score (Coelli *et al*., 1998; Kerstens and Euckaut, 1999). These two different models will be discussed piecemeal next.

6.2.1 The constant returns to scale model

The CRS model assumes a production process in which the optimal mix of inputs and outputs is independent of the scale of operation (Coelli *et al*., 1998). The following CRS model measures overall technical efficiency for each of the sampled farms. The objective function is to maximize the efficiency score $h0$ for farm $j0$, subject to the constraints that no farm will be more than 100%

efficient and the coefficient values are positive and non-zero, when the same set of u and v coefficients (weights) are applied to all other farms being compared.

6.2.2 The variable returns to scale model

The VRS model, though similar to the CRS model, measures pure technical efficiency and returns to scale for each of the sampled farms. Scale efficiency can be measured by dividing the CRS efficiency score by the VRS efficiency score.

There are various ways of looking at RTS and one of them is using an input-oriented measurement and restricted to the optimal projection point. Following Lovell (1994) the preceding VRS technology can be represented by:

$$\begin{aligned} &\mathrm{CRS} \Leftrightarrow \mathrm{DF}_i\left(x, y \middle| \mathrm{CRS}\right) \\ &= \mathrm{DF}_i\left(x, y \middle| \mathrm{NIRS}\right) = \mathrm{DF}_i\left(x, y \middle| \mathrm{VRS}\right) \le 1; \end{aligned} \tag{6.4}$$

$$\begin{aligned} &\mathrm{IRS} \Leftrightarrow \mathrm{DF}_i\left(x, y \middle| \mathrm{CRS}\right) \\ &= \mathrm{DF}_i\left(x, y \middle| \mathrm{NIRS}\right) \prec \mathrm{DF}_i\left(x, y \middle| \mathrm{VRS}\right) \le 1; \end{aligned} \tag{6.5}$$

$$\begin{aligned} &\mathrm{DRS} \Leftrightarrow \mathrm{DF}_i\left(x, y \middle| \mathrm{CRS}\right) \prec \mathrm{DF}_i\left(x, y \middle| \mathrm{NIRS}\right) \\ &= \mathrm{DF}_i\left(x, y \middle| \mathrm{VRS}\right) \le 1. \end{aligned} \tag{6.6}$$

The characterisation presented above is better explained diagrammatically as illustrated in Figure 20, where the observation b and the input-oriented projection of observation e are undoubtedly characterised by constant returns to scale (CRS). It can also be seen that observation c is subject to decreasing returns to scale (DRS) and observation d is subject to increasing returns to scale (IRS).

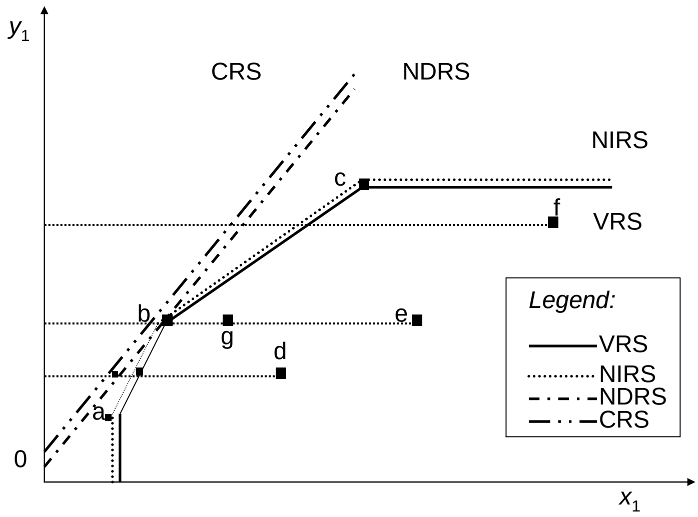


Figure 20: Returns to scale representation of individual observations on DEA

Source: Adapted from Coelli *et al*. (1998:152); Kerstens and Eeckaut (1999)

It can be seen for observation d that:

$$\mathrm{DF}_i\left(x, y/\mathrm{CRS}\right) = \mathrm{DF}_i\left(x, y/\mathrm{DRS}\right) \prec \mathrm{DF}_i\left(x, y/\mathrm{VRS}\right). \qquad \textbf{(6.6)}$$

An important observation to make in Figures 19, 20 and 21 is that part of the conical hull is in common to both CRS and NIRS technologies and the difference with the VRS efficiency score implies that VRS technology is the most appropriate meaning that it fits best (Kerstens & Eeckaut, 1999). Thus, it can confidently be stated that point d is located on the increasing returns to scale part of VRS technology.

For point f the following can be observed:

$$\mathrm{DF}_i\left(x, y \middle| \mathrm{CRS}\right) < \mathrm{DF}_i\left(x, y \middle| \mathrm{NIRS}\right)$$
$$= \mathrm{DF}_i\left(x, y \middle| \mathrm{VRS}\right) \qquad \textbf{(6.7)}$$

The above observation implies that CRS can be rejected in favour of NIRS. Thus it can be inferred that point f is subject to decreasing returns to scale.

The Data Envelopment Analysis (DEA) approach adopted in this chapter to study the KwaZulu-Natal Midlands dairy farm efficiency follows Charnes, Cooper, and Rhodes (Charnes *et al.,* 1978, hereafter referred to as CCR) model with both input and output orientation (Figure 21). Input orientation simply means that DEA inefficiency is estimated in terms of inputs as opposed to the output(s) (Stokes *et al*., 2007). The input oriented approach is generally preferred in most studies probably because it makes more sense in production economics as the producer is generally assumed to be interested in producing a given output level while minimising input use. Moreover, adopting an output orientation (stating inefficiencies in terms of output maximisation subject to fixed input levels) does not change the CRS results.

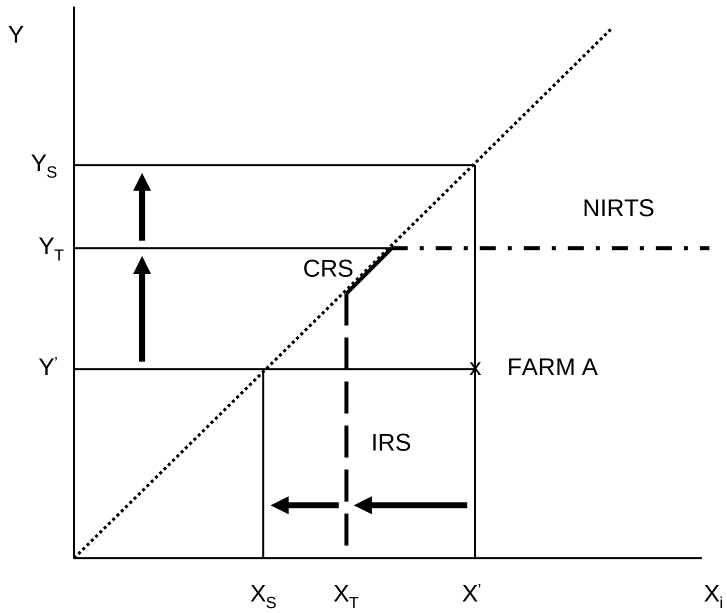


Figure 21: Returns to scale with output and input orientation

The limitations of DEA concern the implicit assumption that all differences in performances of different farms are caused by inefficiencies (e.g. errors in measurement could be interpreted as inefficiencies). In addition, since efficiency is measured relative to other DMUs, these should be comparable in terms of production technologies, input requirements and output mix. In the current study this is ensured by the selection of a homogeneous sample of farms and the exclusion of less specialised enterprises. In general the number of efficient farms increases the more inputs and outputs are distinguished and the fewer farms are compared within the sample. Dyson *et al.* (2001) suggest that to achieve a reasonable level of discrimination, the number of DMUs should be at least twice the product of the number of inputs and outputs. It should be noted that there is no general consensus as to the optimum number of DMUs in relation to the number of variables used. Other researchers suggest that there should be at least three times the number of DMUs as are variables (see Osman, 2010). However, established DEA practitioners caution against being fixated on a hard and fast rule of thumb and suggest that there is no optimum ratio but that the number of DMUs to the number of variables should always be determined by the data available and the sample (Banker, 2010; Ray, 2010; Førsund, 2010; and Paradi, 2010). Furthermore, Banker (2010) advises that the main concern should be whether the sample is representative of the population for which inferences will be made or not.

6.3 Basic DEA results

The results presented start with 31 farms and later on this number of farms is reduced to 17. The choice of using only 17 farms was informed by the fact that the data have to be a balanced panel in order to run the Malmquist index analysis in the Data Envelopment Analysis Programme (DEAP) which will be done in Chapter 7. Thus, only those farms that appeared in all the years (1999 to 2007) are analysed later and these are the same farms for which the Malmquist index will be calculated. Table 44 shows the results of an input orientated DEA for the nine years under the CRS assumption estimated as a pooled sample with all the years in together.

The technical efficiency scores indicate distances away from the frontier thus aptly termed distances in the DEA output files. The results for each year are presented per column for clarity purposes. The results show that 14 out of 31 farms were efficient in using their inputs for milk production in 1999. That is, 14 (45%) farms in 1999 had no input or output inefficiencies resulting in them having DEA efficiency scores of 1. Thus these 14 farms define the efficient frontier and represent the best practice for combining cows, labour, feed, milking, and other machinery to produce milk and other income (output). The mean technical efficiency was 0.89. In 2000 the number of efficient farms decreased from 14 to 11 but with a slightly higher overall efficiency of 0.9 compared to 0.89 the previous year. Of the 11 efficient farms, seven were repeat frontier farms, that is they were also part of the farms that defined the frontier in 1999 and only four were efficient for the first time.

In 2001 the mean efficiency of the farms fell to 0.79 and remained almost unchanged in 2002 (0.76). Most of the farms in these two years were below the frontier, thus inefficient in their allocation of the resources at their disposal.

Table 44: Constant returns to scale (CRS) TE year on year (1999 to 2007)

farm no.	Year								
	1999	2000	2001	2002	2003	2004	2005	2006	2007
1	0.854	0.853	0.844	0.61	0.601	0.79	0.755	0.912	0.999
2	1	0.992	1	0.485	0.5	0.884	1	0.827	0.838
3	0.965	1	1	0.97	0.426	1	0.896	0.935	0.651
4	1	1	0.664	0.828	0.519	0.764	0.561	0.585	0.887
5	0.965	0.933	0.932	1	0.408	1	0.885	1	0.665
6	1	1	0.661	0.794	0.572	0.845	0.664	0.729	0.892
7	0.713	0.793	0.703	0.681	0.437	0.622	0.526	0.535	0.636
8	1	1	0.822	0.435	0.376	0.722	0.988	1	0.982
9	1	0.796	0.96	1	0.518	0.729	1	1	1
10	0.447	0.589	0.482	0.953	0.214	0.379	0.337	0.346	0.554
11	1	0.843	0.529	0.377	0.459	0.698	0.576	0.609	0.919
12	1	1	0.831	0.482	0.423	0.6	0.629	0.818	0.852
13	1	1	1	1	0.456	0.769	1	1	1
14	0.909	0.896	0.716	0.897	0.386	0.903	0.895	1	1
15	1	0.971	0.692	0.417	0.382	0.788	0.697	0.95	1
16	0.879	1	0.815	0.899	0.513	1	0.596	1	1
17	0.741	1	0.657	0.645	0.536	0.767	0.882	0.821	0.702
18	0.957	0.959	0.888	1	1	1	1	1	1
19	0.793	0.989	1	1	0.358	0.717	1	1	1
20	0.885	0.806	0.818	0.837	0.363	0.646	0.821	0.91	0.825
21	0.813	0.846	0.599	0.431	0.393	0.634	0.511	0.595	0.682
22	0.717	0.777	0.658	0.533	0.411	0.715	0.729	0.816	0.809
23	1	1	0.66	0.769	0.358	0.761	0.877	0.864	1
24	0.859	0.866	1	0.998	0.289	0.603	0.715	0.605	1
25	1	1	1	1	0.38	0.688	1	1	1
26	1	0.875	0.638	0.606	0.307	0.768	0.813	0.783	0.926
27	1	0.935	0.802	0.862	0.361	0.744	0.676	0.696	0.851
28	0.84	0.975	1	0.759	0.448	0.823	0.449	0.648	0.521
29	0.176	0.284	0.233	0.332	0.234	0.512	0.411	0.381	0.556
30	0.953	1	0.843	0.927	0.425	0.648	1	1	1
31	1	0.995	0.916	0.959	0.36	0.592	1	1	1
mean	**0.886**	**0.902**	**0.786**	**0.758**	**0.433**	**0.745**	**0.771**	**0.818**	**0.863**

There were only seven efficient farms in 2001 and six in 2002. Only two farms (farm 13 and farm 25) were able remain efficient throughout the four years, rendering best practice farms thus suitable for being used as benchmarks for the sample.

The following year, 2003 was the worse year in terms of the number of inefficient farms and the overall efficiency of the farms in the region. To begin with, there was only one farm that operated on the frontier and interestingly, it was not one of those farms that had consistently performed well thus far. Secondly, the mean efficiency fell to a very low 0.43, which was less than half the efficiency scores attained both in 1999 and 2000. The possible causes of this slump will be discussed later in this chapter.

The efficiency of the dairy farms studied began to improve consistently from 2004 until the end of the period when they regained levels similar to those for 1999 and 2000. The salient points in these results are that both farm 13 and 25 were the overall leaders in terms of efficiency among their counterparts in the sample. The other prominent observation is that farm 18, which emerged strong when all the other farms experienced a dismal year in 2003, continued to be on the frontier until the end of the observation period 2007. Actually, farm 18 attained full efficiency in 2002, the year before the mean efficiency plummeted. A look at the data reveals that farm 18 was a relatively large farm but with low cost of operation, and this is probably why it emerged as efficient when all the other farms were hit by high cost of production as input costs increased drastically.

Drawing a conclusion from the results discussed thus far, it seems that the improvement observed in efficiency can largely be ascribed to the increased number of efficient farms rather than improved (higher) individual efficiency scores. Figure 22 shows that the technical efficiency of the dairy farms declined overall, though there is a small variation around the mean. There was, however, a marked decline in technical efficiency that started in 2001 and culminated in 2003. The decline in 2001 was remarkable when compared to the previous year. In 2000 TE was 0.902, declining to 0.786 in 2001, a 13 percent slowdown. However, the decline that started in 2001 hit its lowest point in 2003 when TE was a mere 0.433 or a decline of 52 percent when compared to the 2000 level. In 2004 TE improved substantially from the 0.433 (in 2003) to 0.745, just below the 2002 level, and thereafter the farms exhibited a steady increase in TE until 2007.

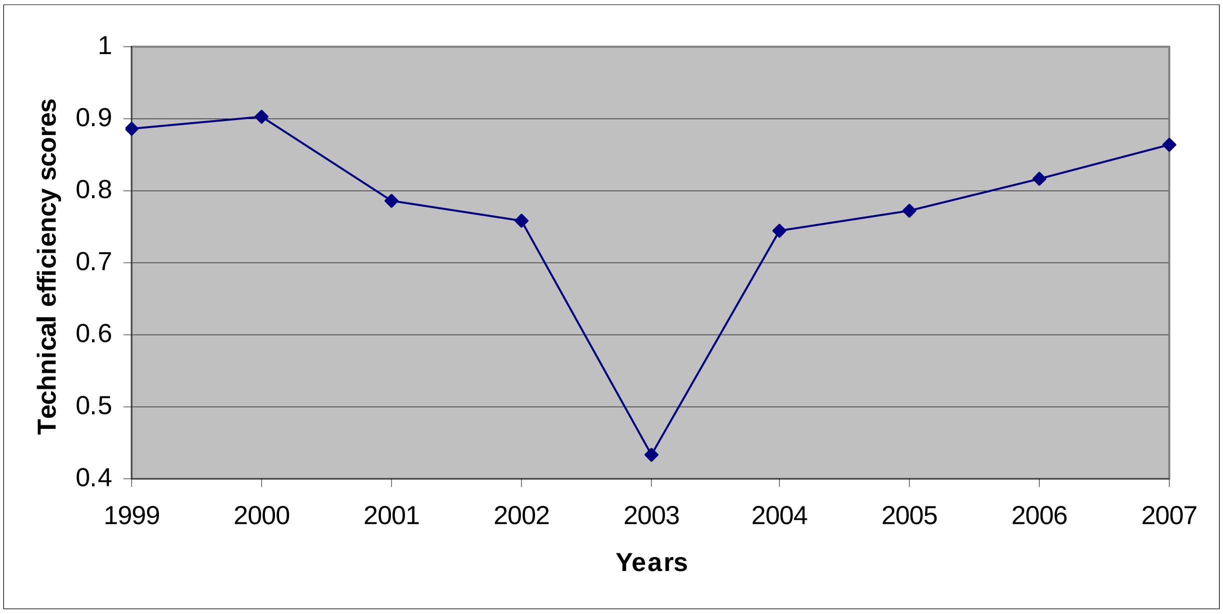


Figure 22: Mean CRS technical efficiency scores

There are two plausible explanations for this decline:

1. The KwaZulu-Natal Midlands experienced a drought period that started towards the end of 2000 and continued until 2003. This drought meant that farmers had to irrigate their pastures more, given that the dairy farming in the region is pasture-based. Increased irrigation entails increased operating costs in the form of electricity and/or diesel used for pumping water and the labour requirements attendant to this activity. For those farmers that could not afford to increase their cost of production, this meant that there was reduced pasturage and limited silage that was available for feeding the cows, a combination of which invariably leads to lower levels of milk production.

2. In 2001 input costs rose uncharacteristically in South African agriculture. The price of fertiliser, fuel, herbicides and pesticides showed the highest increase. This could have been a result of increased petroleum prices, given that all these inputs are petroleum based and are, by and large, imported. However, the problem for dairy farmers was compounded by the fact that the price of milk (output) did not match the increase in the cost of production. In fact, the milk price declined in real terms during this period. The unfavourable production conditions were further exacerbated by the weak exchange rates (weakening of the South African Rand against the US Dollar) which contributed, in part, to higher input prices since the majority of dairy production inputs are imported (Sandrey and Vink, 2008).

Given that there are two assumptions under which the DEA can be done, that is CRS and VRS, Table 45 shows similar results to those presented in Table 44, the only difference being that the results in Table 45 are under the variable returns to scale (VRS) assumption as opposed to the constant returns to scale (CRS) assumption.

Figure 23 shows the mean technical efficiency (TE) of the 31 farms over the nine years of observation under variable returns to scale (VRS). A similar pattern as that depicted in Figure 22 is shown here. However, under VRS, the TE of the farms is much higher than when constant returns to scale are assumed. The implication of the higher TE scores when the constant returns to scale assumption is relaxed is that, in reality, there are variable returns to scale within the sample. It is interesting to note that the trend is similar under both CRS and VRS, which is not surprising given that the farm identities remain the same.

Table 45: Variable returns to scale (VRS) TE year on year (1999 to 2007)

farm no.	Year								
	1999	2000	2001	2002	2003	2004	2005	2006	2007
1	1	0.893	0.885	0.665	0.801	0.794	0.895	0.943	1
2	1	1	1	0.755	0.762	1	1	1	0.961
3	1	1	1	1	0.448	1	0.95	1	0.654
4	1	1	1	1	1	1	1	1	1
5	0.97	0.946	1	1	0.511	1	0.888	1	0.666
6	1	1	0.818	0.794	0.644	0.85	0.667	0.742	0.897
7	0.753	0.875	0.813	0.69	0.562	0.666	0.532	0.557	0.657
8	1	1	0.882	0.777	0.79	1	1	1	1
9	1	0.816	1	1	1	1	1	1	1
10	1	1	1	1	1	0.977	0.974	0.87	1
11	1	0.912	0.905	0.666	0.781	0.815	0.913	0.835	1
12	1	1	1	1	1	1	1	1	1
13	1	1	1	1	0.488	0.778	1	1	1
14	0.961	0.95	0.818	0.975	0.745	1	1	1	1
15	1	0.973	0.724	0.702	0.606	0.945	0.867	1	1
16	1	1	1	1	1	1	1	1	1
17	0.745	1	0.665	0.685	0.673	0.834	0.918	0.854	0.775
18	1	1	1	1	1	1	1	1	1
19	0.793	1	1	1	0.741	0.894	1	1	1
20	0.996	0.896	1	1	0.478	0.671	0.837	0.92	0.835
21	0.878	1	0.96	0.962	0.963	0.971	0.989	0.884	0.819
22	0.724	0.796	0.658	0.538	0.628	0.763	0.745	0.817	0.812
23	1	1	0.707	0.8	0.634	0.888	0.957	0.873	1
24	1	1	1	1	1	1	1	1	1
25	1	1	1	1	0.667	0.856	1	1	1
26	1	0.881	0.642	0.61	0.401	0.792	0.815	0.809	0.95
27	1	0.949	0.853	0.896	0.567	0.891	0.736	0.745	1
28	0.843	0.978	1	0.882	0.842	0.953	0.787	0.874	0.767
29	0.359	0.287	0.31	0.339	0.312	0.53	0.434	0.381	0.585
30	1	1	0.862	0.965	0.866	0.938	1	1	1
31	1	1	1	1	0.449	0.607	1	1	1
mean	**0.936**	**0.94**	**0.887**	**0.861**	**0.721**	**0.884**	**0.9**	**0.907**	**0.915**

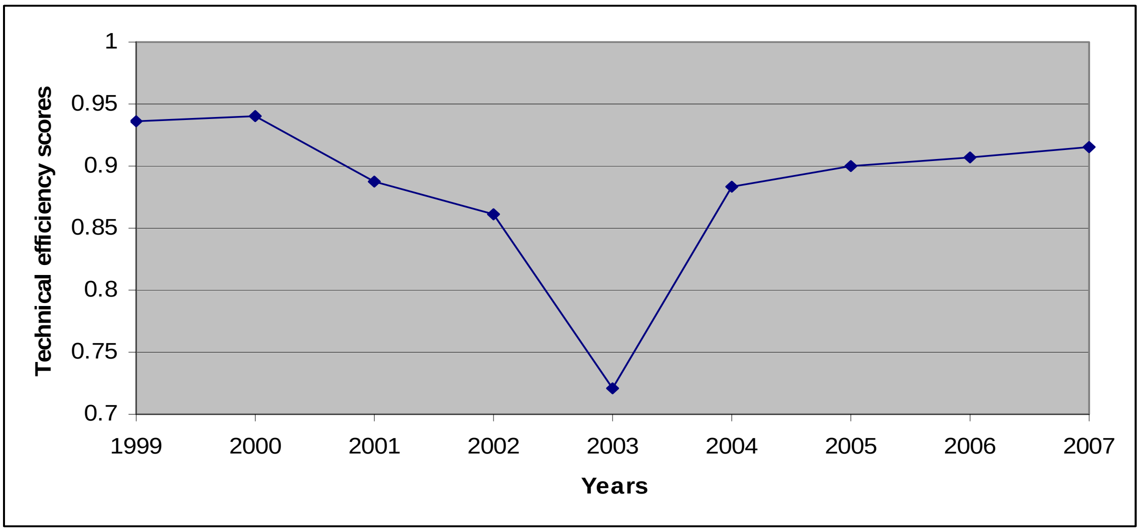


Figure 23: Mean VRS technical efficiency scores

Figure 24 is a juxtaposition of technical efficiency scores under both CRS and VRS. The purpose of this figure is to give a visual comparison of the levels of efficiency achieved under the two returns to scale assumptions and to further buttress the notion that there are returns to scale for the dairy farms in the KwaZulu-Natal Midlands. Scale efficiency is obtained by dividing CRS technical efficiency by VRS technical efficiency (SE=TEcrs/TE vrs) thus the wider gap in 2003 is mostly a fall in scale efficiency. So is it more IRS that is the cause. This is a different take on RTS as it gives a scale efficiency score for each farm. The reason for the increasing returns to scale could be that bigger farms have better water access and access to better soils as they can decide where to cultivate their pastures on the farm.

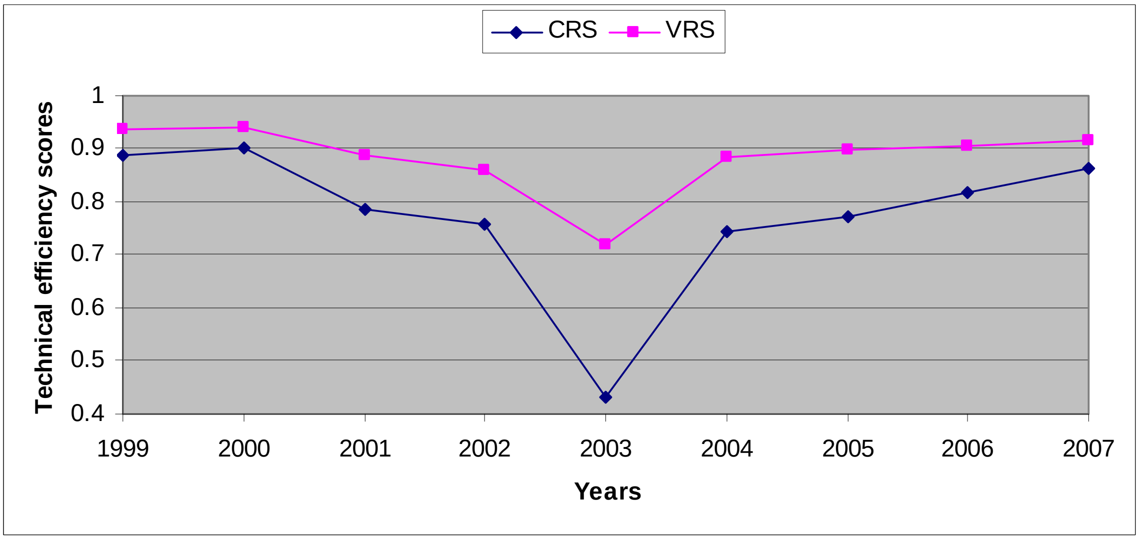


Figure 24: Mean technical efficiency scores: CRS and VRS assumption

Having looked at the individual farms over the individual years, the next logical step is to look at the composite picture by analysing the changes in efficiency as a function of the passage of time. It should be noted that the difference between CRS efficiencies and VRS efficiencies is scale inefficiency being taken out in the former.

6.4 Input and output slack results

With the results from DEA studies, management can make changes where inefficiencies exist. Inefficiencies in inputs or a shortfall in produced outputs generate slacks. Thus, slacks can be defined as the existence of excesses in inputs and shortfalls in outputs (Tone, 1999). These slacks reflect either surpluses (inputs) or shortages (outputs) in the production of services. Slacks can be analyzed to determine which inputs or outputs contribute most to a unit's computed efficiency scores (Ozcan, 1995). For each decision-making unit or farmer (in this case), DEA slack values quantify the amount of excess inputs it is using to produce the same output as its peers (Ozcan, 1995; Watts *et al*., 1998). The farmers' management can use these results to contain and/or reduce costs in their farming operations. The results can also be used by policy makers in priority assessment for planning and policy (Ozcan, 1995).

There were no output slacks, as this analysis was input orientated. Input orientation DEA does not yield output slacks because the focus is on measuring the efficiency of employing the inputs at the firm's disposal to achieve the output measured. Table 46 shows a summary of input targets as this is useful in putting the slacks results in perspective. Input targets refer to the average desirable level of each input that each farm should use to produce the desired level of output optimally.

Table 46: Summary of input targets for the dairy farms in the sample

Farm	Land	Labour	Feed	Veterinary	Milking machinery	Other machinery
1	285	24919	43971	11660	20568	13493
2	77.148	6926.501	13931.07	3168.865	5373.018	3769.545
3	96.201	8693.373	81653.41	7678.477	8544.394	3651.327
4	135.439	11932.81	21867.74	5537.733	9657.313	6453.692
5	122	9904	518672	31444	15377	5288
6	124	15247	96273	11493	16626	19535
7	86.433	7461.679	75979.91	6851.425	7061.469	4030.938
8	88.837	7356.895	282671.9	17868.57	9947.847	3943.341
9	108	8138	201422	35182	10141	732
10	90.173	7689.652	141411	10436.59	8184.115	4144.679
11	138.088	12971.4	100351	10359.02	12505.15	9554.113
12	202	20630	102173	13680	21306	2780
13	216	24987	98713	8608	7705	13017
14	193.971	17199.35	71853.46	10311.46	14996.95	10064.35
15	132.162	14596.47	48413.72	5463.739	8005.308	8291.016
16	182.091	20526.17	45172.07	6519.72	16713.28	11226.27
17	200	33311	81035	4787	29218	18553

Table 47 presents the DEA results. Seven out of the 17 farms were found to be DEA efficient with an efficiency score of 1. In other words the seven efficient farms had no possible radial reduction (radially efficient) and no slacks. This means no radial reductions are possible and there are no slacks. Given the nature of the DEA approach, the seven farms define the efficient frontier and so they represent the best practice farms for combining land, labour, feed, veterinary services, milking and other machinery to produce the intended output (income from the sale of milk and animals). The rest of the farms (10) had efficiency values less than one, indicating inefficiencies in the use of some inputs. The average efficiency level of the farms was found to be 0.867 and ranged from 0.351 to 1.000.

The next important step is to look at the input slacks. Milking machinery and other machinery represent capital usage as the data did not include the total value of capital, as discussed earlier. Most of the farms (12 out of 17) were efficient in terms of farm size (number of cows) and only five had slacks. This seems to suggest that these five farms were operating at more than optimal size (as measured by herd size), implying that they can improve efficiency by reducing farm size by the value indicated by the slack. The overall mean 'excess capacity' was 16.711, representing 17 cows above the optimum size on average. The picture is somewhat similar with regard to labour costs, which represents labour utilisation by the farms. Here only four farms had inefficiencies in labour utilisation while 13 were at the frontier and thus could be viewed as benchmarks. For purchased feed, 6 farms had slacks but this is not the most interesting point. What is worth mentioning is that the variation or deviation from the 'ideal' level of purchased feed expenditure is highest of all the variables. On average, the farms that were found to be inefficient in the utilisation of this input used over R13 000 more than the frontier value. The most inefficient farm recorded a value of R97 335.04 more than the optimal level. The implication for this farm (farm 8) is that it is possible to save R97 000 while producing the same level of output.

Table 47: DEA results, ranked by efficiency scores with slacks for six inputs

Farm	**Efficiency**	**Land (ha)**	**Labour (R)**	**Feed (R)**	**Veterinary (R)**	**Milking machinery (R)**	**Other machinery (R)**
1	1.000	-	-	-	-	-	-
5	1.000	-	-	-	-	-	-
6	1.000	-	-	-	-	-	-
9	1.000	-	-	-	-	-	-
12	1.000	-	-	-	-	-	-
13	1.000	-	-	-	-	-	-
17	1.000	-	-	-	-	-	-
10	0.999	12.715	-	59102.31	11168.95	-	411.374
11	0.966	-	6178.35	-	10284.59	1241.802	-
7	0.935	109.902	-	-	10173.66	5232.865	6599.219
4	0.861	45.361	-	39228.94	5737.311	-	1181.241
14	0.886	0	309.412	13527.42	-	3094.61	-
8	0.82	74.43	-	97335.04	119413.4	-	5607.413
16	0.799	41.679	-	3788.165	-	-	4024.503
15	0.635	-	954.122	-	-	-	1088.645
3	0.481	-	354.375	-	9.945	1089.222	-
2	0.351	-	-	9723.954	4202.64	-	251.977
mean	**0.867**	**16.71**	**458.60**	**13100.34**	**9470.03**	**626.97**	**1127.32**

Note: - Indicates no surplus input, i.e. efficiency in the use of that particular input

The second highest average slack value was with veterinary expenditure. This is an interesting variable in the sense that, in most cases, the use of veterinary services is outside the planning control of the farmers, as the bulk of veterinary expenses, excluding artificial insemination, are largely necessitated by unforeseeable conditions such as the outbreak of a disease. Thus it is difficult to fully and fairly attribute this deviation to inefficiency of the farm proprietor. However, there are preventative steps that the farmer can take and thus be proactive and pre-empt health disorders. For milking machinery, only four out of the 17 farms exhibited surplus use of this variable. The implication here could be that the farms have unexploited capacity to milk more cows using the existing infrastructure. Lastly, there were seven farms with slacks for the other machinery which represent the highest number of inefficient farms for an individual variable. This is not surprising given that it is difficult to allocate this variable to different farming activities. It is safe to claim that this variable is used to produce some of the other inputs in the production system, such as carting the purchased feed around the farm and moving bulk tanks for the milk (this is technically accounted for under milking machinery). Other machinery can also be viewed as complimentary to labour as some of workers drive tractors and operate other machinery on the farm. Investments in machinery are lumpy requiring an initial fixed cost that might make small adjustments in capacity infeasible.

Among the inefficient dairy farms, feed and veterinary expenditure were most often used in excess of the requirements of the system to achieve an efficient level of production. On average, only for the farms with inputs slacks and not the whole sample, feed was over-used by R13 100.14 per farm and expenditure on veterinary services by R9 470.04.

One of the most striking features of the DEA is that it makes it possible for a farmer to identify ways of changing the input mix to achieve an efficient level of production. For example, Farm 10 has a radial DEA efficiency score of 0.999, implying that it should decrease its use of land, feed, expenditure on veterinary expenses and other machinery by only 0.1 percent (that is 1-0.999) as the first measure toward becoming efficient. To state this differently, Farm 10 can achieve its current level of production by using 99.9 percent of its current inputs level. The next step in improving efficiency (reducing inefficiency) would be to look at the individual inputs which were used in excess of the desired level. Looking at the land variable in table 48, Farm 10 should adjust land downward by 12.715 ha as shown by the slack on this input. Similarly, feed, expenditure on veterinary services and other machinery would have to be adjusted downwards (by R59102.31, R11 168.95 and R411.37 respectively). Generally speaking, target levels of production (output) can be realised by employing less land, feed, veterinary expenses and other machinery than current levels of use. It is also useful to look at the least efficient farm as an example of how to use the DEA results to improve efficiency levels. The least efficient farm in the sample is Farm 2, with a DEA score of 0.351. Given the efficiency score of 0.351, it stands to reason that the first step toward achieving full efficiency would be to adjust all the inputs with slacks to about 35 percent or reduce these inputs by about 65 percent of the current levels used.

In these two examples the challenge facing the farmers is to alter the level of inputs in order to achieve efficient levels of production. Admittedly, it is not always easy for farmers to change levels of inputs given the fixed and quasi-fixed nature of some the inputs used in dairy production, for example land.

As discussed earlier, one other useful attribute of the DEA approach is that it facilitates benchmarking. Benchmarking is an important tool for inefficient farms to improve the efficiency of their production level. Producers and policy-makers, alike, battle with the age old question of what level of input utilisation to use as the standard against which all input utilisation levels should be compared (used as *ordinance datum* – benchmark). For example, using the average farm size (land) of the sample as a benchmark is tantamount to using any other average such as the provincial or national farm size average. However, using the DEA circumvents this shortcoming by identifying the actual efficient farm that each inefficient farm can be compared against rather than some arbitrary average. Identifying a set of benchmarks for an inefficient farm makes it possible for the inefficient farm to observe how these efficient benchmarks (often referred to as peers) use their inputs and learning from them as best practice cases. Table 48 presents the top two benchmarks for each of the inefficient farms.

Table 48: Benchmark dairy farms for the inefficient farms

Rank	Farm	Benchmark #1 Farm	Benchmark #2 Farm
8	10	5	
9	11	5	6
10	7	5	
11	4	13	
12	14	5	6
13	8	5	
14	16	13	17
15	15	13	6
16	3	12	5
17	2	6	13

If Farm 10 is used as an example, Farm 5 is its best benchmark to model itself against in its bid to become fully efficient. In other words, Farm 10 should emulate the way Farm 5 does its business thus rendering Farm 5 the ideal benchmark for Farm 10. In this regard, Farm 10 is 90.17 ha in size, spending R7 686.65 on labour and receiving an income of R162 227 from its production, whereas Farm 5 is 122 ha in extent, spending R9 904 on labour to realise an income of R22 6053.

6.5 Conclusion

The results reported in this chapter were obtained using DEA for studying the production efficiency of a sample of dairy farms from the KwaZulu-Natal Midlands in South Africa. It is worth reiterating that the DEA is a nonparametric linear technique that has the capacity to handle more than one input and outputs. The DEA readily identified specific input inefficiencies for the dairy farms in the sample. Firstly, seven out of the 17 farms were DEA efficient meaning these farms had no possible radial reduction and no slacks. This further means no radial reductions are possible and there are no slacks. Thus, the seven farms define the efficient frontier and so they represent the best practice farms for combining land, labour, feed, veterinary services, milking and other machinery to produce the intended output (income from the sale of milk and animals). The rest of the farms (10) had efficiency values less than one, indicating inefficiencies in the use of some inputs. The average efficiency level of the farms was found to be 0.867 and ranged from 0.351 to 1.000 and too much feed and veterinary services were used by the inefficient farms. Secondly, the identification of those inputs that are over-utilised helps in identifying different production trajectories for the inefficient dairy farms to become efficient. Lastly, the DEA approach has the advantage of being able to identify the most appropriate benchmarks for the inefficient farms to imitate.

Chapter 7: The Malmquist TFP index

7.1 Introduction and background to the Malmquist TFP Index

Chapter 6 provided some background on the use of DEA in measuring the efficiency of dairy farms. Chapter 7 deals with the measurement of the total factor productivity index following the Malmquist method as applied through DEA (Coelli *et al*., 1998). The Malmquist Total Factor Productivity (TFP) index methodology was selected because it does not need prices to get weights and the data used do not have prices for individual inputs, as will be discussed later in this chapter.

The Malmquist TFP index can be defined as a measurement of the TFP change between two data points achieved by calculating the ratio of the distances of each data point in relation to a common technology (Coelli *et al*., 1998:223). The Malmquist TFP index methodology can be traced back to the seminal work of Nishimizu and Page (1982) and Färe *et al.* (1994). It is worth noting that the Malmquist productivity index allows for the separation of a change in efficiency from a change in technology for a given firm (Trueblood and Coggins, undated). The Malmquist output-orientated TFP change between period s (the base year) and period t is given by

$$m_o(y_s, x_s, y_t, x_t) = \left[\frac{d_o^s(y_t, x_t)}{d_o^s(y_s, x_s)} x \frac{d_o^t(y_t, x_t)}{d_o^t(y_s, x_s)} \right]^{1/2}, \qquad \textbf{(7.1)}$$

where x_t represents the input vector and period t and y_t represents the output vector at period t. $m_o(y_s, x_s, y_t, x_t)$ is the minimal output deflation factor, such that the deflated output vector for the firm in period-t, $y_t / [m_0^s(\cdot)]$, and the input vector, x_t, are just on the production surface of the technology in period-s. If firm t has a higher level of productivity than is implied by the period=s technology then $m_0^s(\cdot) > 1$ (Coelli *et al*., 1998:123).

Their non-parametric Malmquist Productivity Index is based on the construction of a piecewise linear frontier using the DEA linear programming method. The DEA is used to calculate and decompose the Malmquist Index of total factor productivity (TFP) growth into technical change, change in technical efficiency and change in scale efficiency. This decomposition allows the identification of the sources of productivity growth which is crucial for policy formulation (Mahadevan, 2002).

The Malmquist productivity index is enticing to use as it does not require any behavioural assumptions about the production units which are usually implicit in economic models of cost minimisation or revenue maximisation. This distinguishing feature is particularly handy if the objectives of producers differ or are unknown. The Malmquist Productivity Index also does not require any data on prices, which in the case of this study are unknown. Most importantly, the index decomposes productivity change into two components, namely technical efficiency change and technical change. The construction of the Malmquist Index involves the measurement of technical efficiency, technical progress and efficiency change. The combination of the change in technical efficiency and technical progress creates a measure of the change in TFP, which is the Malmquist productivity index. Analysis of technical efficiency is based on cross-sectional estimation of efficiency measures, relative to the best-practice frontier for each year. By adding the time series dimension it is possible to estimate the shifting of the frontier over time, giving a measure of pure technical progress. Thus, inter-temporal and inter-firm distance functions form the Malmquist TFP index. The Malmquist index is an original index of productivity change. In contrast to the Tornqvist index, the Malmquist index does not require cost or revenue shares to aggregate inputs and outputs, yet is capable of measuring TFP growth in a multiple output setting.

The input-based Malmquist productivity change index as the geometric mean of adjacent period Malmquist productivity indexes can be expressed as follows. Following Färe *et al.* (1992), the Malmquist productivity index for district *i* between period *s* and *s+1* is defined as

$$M_i^{s,s+1} = \left(\frac{D_i^s(y^t, x^t)}{D_i^{s+1}(y^{t+1}, x^{t+1})} \right) \left(\frac{D_i^{s+1}(y^{t+1}, x^{t+1})}{D_i^s(y^{t+1}, x^{t+1})} \frac{D_i^{s+1}(y^t, x^t)}{D_i^s(y^t, x^t)} \right)^{1/2} \qquad \textbf{(7.2)}$$

where D_i are input distance functions.

The ratio in the first bracket captures technical efficiency change (TEC) and the ratio in the second bracket provides a measure of technical change (TC). TEC is greater than, equal to, or less than unity as technical efficiency accordingly improves, remains unchanged, or declines between time period *s* and *s+1*. TC is greater than or equal to unity, and shows whether the frontier is improving or stagnant. The value of the Malmquist productivity index is greater than, equal to, or less than unity. If the value of the index is greater than unity, it reveals improved productivity and if the value is less than unity, a decrease in productivity occurs.

The concept of the Malmquist index can be illustrated by considering an example involving farms which use two inputs (x_1 and x_2) in order to produce a single output (*y*), in two periods, *t* and *t+1*, under an assumption of constant returns to scale (CRS) (Figure 25). The frontier at period *t*, L^s, is defined by two efficient countries, A^t and B^t, and the efficiency of a third country, at C^t, is calculated relative to this frontier. The input distance function at period $t, D_i^s(y^t, x^t)$, is equal to OC^t/OF, on the initial vector x^t. In the next period, the frontier has moved to L^{s+1} and farm *C* now has an input ratio x^{t+1} and operates at C^{t+1}. The input distance function at period $t+1, D_i^{s+1}(y^{t+1}, x^{t+1})$, is OC^{t+1}/OG. The ratio of these two distance functions measures the technical efficiency change, shown as the ratio in the first parenthesis in Equation (7.2). The terms in the second parenthesis in (7.3), which is the technical change component, can be defined similarly. $D_i^s(y^{t+1}, x^{t+1})$ is equal to OC^{t+1}/OE, thus, the first ratio in the second bracket is equal to OC^{t+1}/OG divided by OC^{t+1}/OE giving OE/OG.

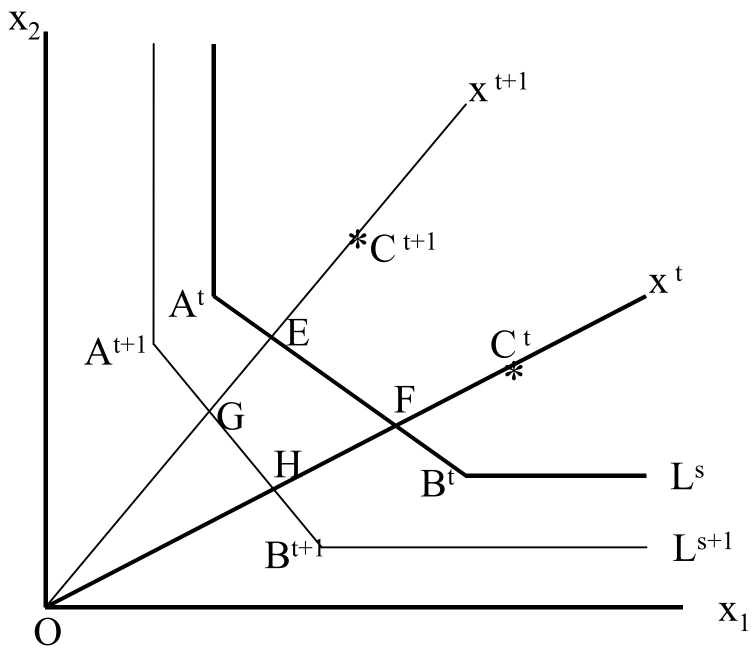


Figure 14: The Malmquist productivity index using input orientation
Source: Fare *et al*., 1992

This is the shift of the frontier measured at the factor ratio of the second period, x^{t+1}. The last term in the second bracket can be defined in a similar manner giving *OF/OH*, which is the shift of the frontier measured at the factor ratio of the first period, x^t. Therefore, in terms of the example shown, the Malmquist productivity index can be defined as:

$$M_i^{t,t+1} = \left(\frac{OC^t / OF}{OC^{t+1} / OG} \right) \left(\frac{OC^{t+1} / OG}{OC^{t+1} / OE} \frac{OC^t / OH}{OC^t / OF} \right)^{1/2} = \left(\frac{OC^t / OF}{OC^{t+1} / OG} \right) \left(\frac{OE}{OG} \frac{OF}{OH} \right)^{1/2} \quad \textbf{(7.3)}$$

TFP is then defined as the product of technical efficiency change (TEC) and technical change (TC). Technical efficiency change is defined as the change in the relative distance of observed inputs from the frontier of technology, and technical change is defined as shifts in the production frontier.

Therefore, the TFP measures changes in the productivity and the direction of the change (that is, whether advancement – above unity or decline – below unity). The DEA approach is employed in the results reported in this chapter. However, it would suffice to say that the stochastic frontier approach can also be used the yield the quasi Malmquist index:

$$EC_{i(t+1)} = \frac{TE_{i(t+1)}}{TE_{it}} \quad \textbf{(7.4)}$$

$$TC_{i(t+1)} = \sqrt{\left\{ 1 + \frac{\partial f\left(x_{i(t+1)}, (t+1), \alpha\right)}{\partial (t+1))} \right\} \bullet \left\{ 1 + \frac{\partial f\left(x_{it}, t, \alpha\right)}{\partial t} \right\}} \quad \textbf{(7.5)}$$

$$MTFP_{it} = EC_{it} \bullet TC_{it} \quad \textbf{(7.6)}$$

7.2 Malmquist TFP Index: results and discussion

Due to the structure of the data set used in this analysis, it was not possible to establish if all resources such as land and labour were utilized by the dairy enterprise. Thus excess resources will be identified in the results as surpluses. The results presented start with 31 farms and later on this number of farms is reduced to 17. The choice of using only 17 farms was informed by the fact that the data have to be a balanced panel in order to run the Malmquist Index analysis in the Data Envelopment Analysis Programme (DEAP). Thus, only those farms that appeared in all the years (1999 to 2007) are analysed. However, because DEA is a nonparametric method the relatively few farms in the dataset are not a major concern statistically. No statistical tests of significance are performed because DEA is not a statistical method that is affected by limited degrees of freedom. The reader should also note that it is not unusual for DEA to be performed on few enterprises (see Ragsdale, 2007) although some writers argue that there should be at least three times as many observations as there are variables. A more thorough discussion was done in Section 6.2.2.

Before delving into the results it is worth defining the various efficiency measures used in the discussion as produced by the DEAP programme. The output from the DEAP for Malmquist analysis yields efficiency change (EFFCH), technical efficiency change (TECHCH), pure efficiency change (PEFFCH), scale efficiency change (SEFFCH), and total factor productivity change (TFPCH) as shown in Table 49.

Table 49: Malmquist Index for the dairy farms from year 2 (2000)

Farm	Efficiency change	Technical efficiency change	Pure efficiency change	Scale efficiency change	Total factor productivity change
1	0.854	1.581	1	0.854	1.351
2	1	1.622	1	1	1.622
3	0.965	1.341	1	0.965	1.295
4	1.03	1.346	1	1.03	1.386
5	0.965	1.547	0.97	0.995	1.494
6	1	1.551	1	1	1.551
7	0.759	1.327	0.782	0.97	1.007
8	1	1.434	1	1	1.434
9	1.075	1.532	1.059	1.015	1.647
10	0.676	1.409	1	0.676	0.952
11	1.177	1.313	1	1.177	1.546
12	1.04	1.687	1	1.04	1.755
13	1	1.576	1	1	1.576
14	1.039	1.326	0.961	1.08	1.377
15	1	1.279	1	1	1.279
16	0.879	1.327	1	0.879	1.166
17	0.858	1.22	0.804	1.067	1.047
18	0.978	1.546	1	0.978	1.513
19	0.84	1.746	0.827	1.015	1.466
20	0.886	1.42	0.996	0.89	1.258
21	0.813	1.489	0.878	0.926	1.21
22	0.905	1.474	0.906	1	1.334
23	1.068	1.32	1.056	1.011	1.41
24	0.886	1.49	1	0.886	1.32
25	1	1.647	1	1	1.647
26	1.114	1.435	1.091	1.021	1.598
27	1	1.422	1	1	1.422
28	0.84	1.417	0.843	0.996	1.19
29	0.806	1.497	1.143	0.705	1.207
30	1.103	1.523	1	1.103	1.681
31	1.036	1.517	1	1.036	1.571
mean	**0.948**	**1.458**	**0.975**	**0.972**	**1.382**

Efficiency change measures the change in basic efficiency over time and it is a function of PEFFCH and SEFFCH as shown in Equation (7.7) and TFPCH is a product of EFFCH and TECHCH (Equation 7.8):

$$\mathrm{EFFCH} = \mathrm{PEFFCH} * \mathrm{SEFFCH} \qquad \textbf{(7.7)}$$

$$TFPCH = EFFCH * TECHCH \quad \textbf{(7.8)}$$

The reporting of the Malmquist Index starts from year 2 (2000 in this case) because of how the index is calculated. The previous year (year 1, 1999) was used as the base year since the index measures annual progression of the efficiency indicators. Another interesting observation is that all the 31 farms posted positive technical efficiency growth in 2000, as shown in the third column, although the efficiency changes (column 2) were not commensurate with this trend. The fact that efficiency change was less than unity for most farms also had a dampening effect on TFP resulting in Farm 10 having a TFP change value of less than unity (column 6). The next focus of the discussion is looking at efficiency changes year by year.

Table 50 shows the changes in efficiency over the years by decomposing efficiency into overall efficiency change, technical change, pure efficiency change, scale efficiency change and total factors of production change. By and large, efficiency was just about constant with slight variations either side of 1. There are four years (2000, 2002, 2003 and 2004) that had decreasing efficiency and year 2004 recorded the lowest efficiency change of 0.578. However, the next year (2005) had the highest efficiency change of 1.759. This high value could be due to the fact that the previous year had the lowest value. The overall efficiency change was 0.993 which is quite close to 1 (efficient level). Technical efficiency is increasing, implying that technological change played a substantial role in increasing production efficiency of the farms. Further, this implies improvement in technology (technological gains) over the study period leading to the conclusion that the farms, on average, are progressively adopting new technology. Both pure and scale efficiencies were slightly less than unity (0.995 and 0.998, respectively), thus their contribution to the overall efficiency of the farms is constant. It is interesting to note that total factor productivity increased over the period with a mean of 1.079.

Table 50: Changes in efficiency for the dairy farms over 9 years

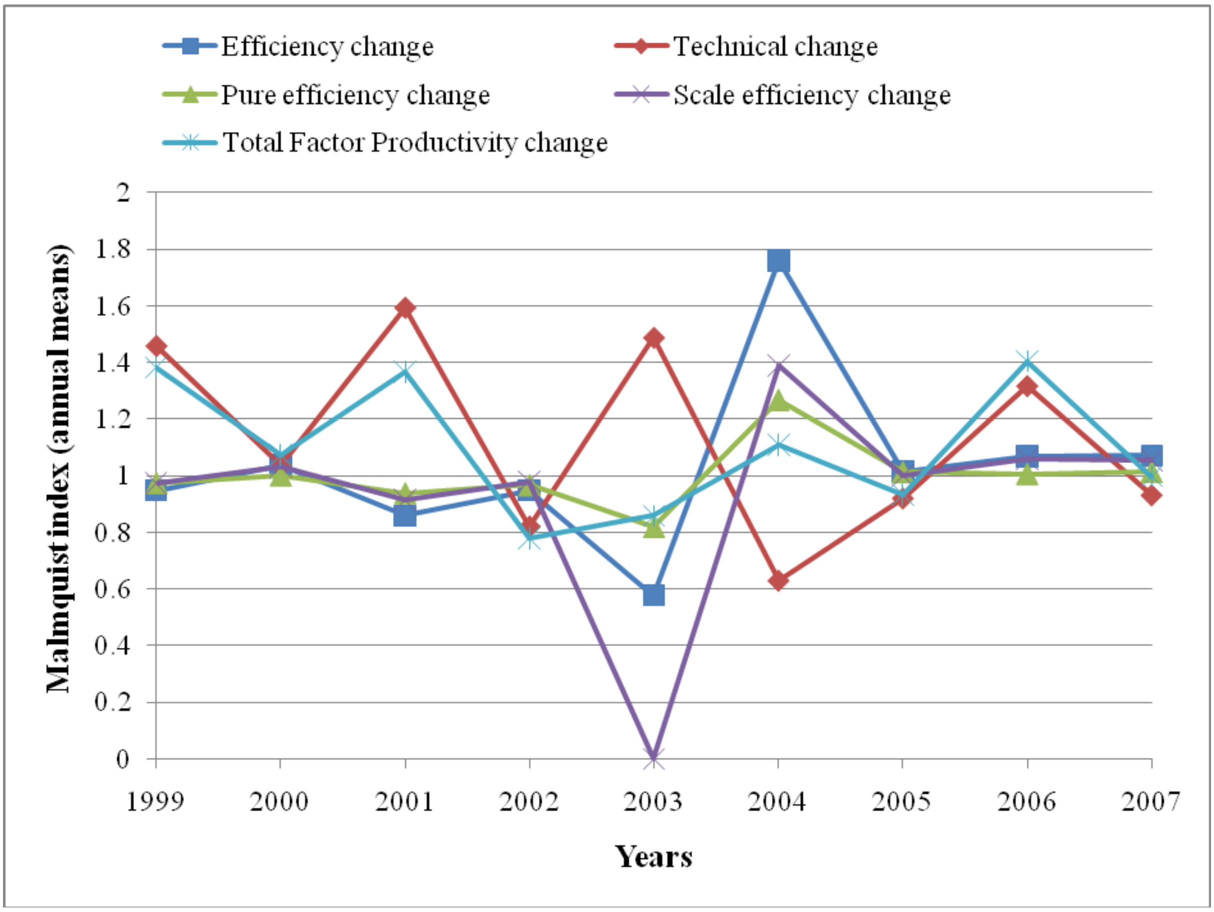
Year	Efficiency change	Technical change	Pure efficiency change	Scale efficiency change	Total Factor Productivity change
1999	0.948	1.458	0.975	0.972	1.382
2000	1.036	1.037	1.002	1.033	1.074
2001	0.859	1.593	0.939	0.914	1.368
2002	0.948	0.822	0.968	0.98	0.78
2003	0.578	1.487	0.821	0.704	0.859
2004	1.759	0.631	1.267	1.388	1.109
2005	1.013	0.921	1.014	1	0.933
2006	1.067	1.317	1.007	1.06	1.405
2007	1.071	0.932	1.015	1.055	0.998
mean	**0.993**	**1.086**	**0.995**	**0.998**	**1.079**

Table 51 shows the same results albeit using a different approach and for fewer farms (17) for more years (9 years), while Table 52 reports the Malmquist index results per individual farm rather than year on year. The Malmquist index approach was used to examine efficiency and productivity between farms. In contrast to conventional production function or other index approaches, the Malmquist approach can distinguish between two sources of productivity growth: changes in technical efficiency and technical change. When applied to panel data, as in the present study, this approach can also identify the innovating farms over time. The Malmquist approach does not require the assumption of efficient production, but instead identifies the 'best-practice' farm in every period, which gives an efficient production frontier, and measures each farm's output relative to the frontier. However, as can be expected, the mean efficiency scores remain virtually the same.

Table 49: Malmquist Index summary of farm means

Farm	Efficiency change	Technical change	Pure efficiency change	Scale efficiency change	Total Factor Productivity change
1	1	1.02	1	1	1.019
2	0.981	1.125	0.996	0.985	1.103
3	0.953	1.127	0.954	1	1.075
4	0.99	1.032	1	0.99	1.022
5	0.956	1.151	0.956	1	1.1
6	0.987	1.03	0.988	0.999	1.017
7	0.958	1.047	0.958	0.999	1.002
8	0.998	1.064	1	0.998	1.062
9	1.008	1.134	1.006	1.002	1.143
10	0.98	1.045	1	0.98	1.024
11	1.009	1.046	1	1.009	1.055
12	0.987	1.037	1	0.987	1.023
13	1	1.18	1	1	1.18
14	1.015	1.071	1	1.015	1.087
15	1	1.02	1	1	1.02
16	1	0.992	1	1	0.992
17	0.977	1.024	0.98	0.997	1
Mean	**0.989**	**1.067**	**0.991**	**0.998**	**1.054**

Figure 26 shows the annual means of the Malmquist Index for the 17 farms from 2000 to 2007, keeping in mind that these are chained results. TFP remained almost unchanged throughout the period, excepting from 2001 to 2003 when there was a marked decline in TFP change. Technical change seemed to be the cause of the declining TFP; this is not surprising as technical change is a component of TFP, thus it is expected that as technical change changes TFP should also take the same direction. The results reported in Table 51 support this assertion. What is surprising, however, is why technical change declined. A plausible explanation could be that this decline coincided with the drought in KwaZulu-Natal. The drought meant that farmers had to rely more on irrigation to produce enough fodder for their herds, and most farmers had to either replenish their existing irrigation infrastructure or purchase new systems and thus had to familiarise themselves with how to efficiently use this technology. It should be noted that dairy farmers in the KwaZulu-Natal Midlands only use supplementary irrigation as required, and are therefore not necessarily proficient in its use.



Note: *Scale assumption: CRS; Single-stage DEA

Figure 15: Annual means of the Malmquist Indices for the farms (2000 to 2007)

7.3 Summary of Malmquist TFP findings

The results compare applied programming techniques to the panel data to produce estimates of efficiency, i.e. the distance of inefficient farms from the frontier, and the separate technical efficiency from scale efficiency. The next stage is the measurement of technical progress, i.e. the shifting of the best-practice frontier over time, a measure that allows Malmquist Indices of TFP to be constructed from the efficiency and technical change measures, without recourse to prices (Hadley *et al*., 1999). It is important to note that the results are presented as chained indices in order for the rate and causes of TFP growth to be analyzed. The Malmquist Index is ideal for investigating TFP growth because it decomposes into technical progress, technical efficiency and scale efficiency measures. Results from

TFP growth analysis can provide insight into the performance of the dairy farms and lead to different policy implications. For example, lack of technical progress implies that more resources must be allocated to research and development (investment in innovation) to generate new technology whereas low technical efficiency implies more and probably better extension services are needed and these should be targeted at those farmers lagging behind (the so called late adopters and laggards). Lastly, low scale efficiencies may be an indication that consolidation of farms is required.

Secondly, average technical efficiency was the only TFP component that posted some increase at some stage of the period of observation, namely during 1999 to 2001, when it increased by 40 percent. This was the period following the completion of the deregulation of the agricultural sector, including dairying, in South Africa. The possible reason for the substantial increase in technical change (technology improvement) posted during this time could have been because dairy farmers were investing more in technology in a bid to position themselves to be competitive in the international dairy market. It appears that the removal of production quotas also played a role in encouraging technological innovation and investment. Another contributing factor to this initial growth in technical change was the considerable investment in the improvement of the dairy herd genetics as illustrated by increased milk production per cow and higher feed conversion ratios which makes the dairy cow an 'efficient milk producer' (ratio of feed/ nutrients consumed and milk produced by the cow). However, the initial boom in technical change was short-lived as technical change then went on a downward spiral for the rest of the years. An aggregate negative technological progress (regression) of 5.03% per annum was observed.

The regression in technical change coincides with the period when land reform gained momentum in South Africa and it is believed that some farmers feared that their farms may be targeted for land redistribution, and were thus wary of investing in expensive technology as they wanted to see the outcome of the land reform process. Another factor was also the introduction of the minimum wage for farm-workers, which resulted in some farmers retrenching some of their workforce. Since no change in labour productivity was measured, this could manifest itself as a decrease in technical change.

Lastly, total factor productivity declined from 1999 up to 2004 and thereafter became stable at lower levels. The decline in the initial phase was largely an aggregate effect of the changes in efficiency and technical changes because these two indicators are components of TFP change. The average annual change in total factor productivity between 1999 and 2007 was -5.27%, indicating an average decline over the years. This is somewhat unexpected because the available literature shows that dairy farmers in the KwaZulu-Natal Midlands have become fewer but bigger in size. The obvious expectation would have been that farms are becoming bigger to take advantages of scale economies; however, the results reported in this chapter attest to the contrary. Thus there are probably other reasons as to why the dairy farms are becoming bigger.

Having dealt with technical efficiency, scale efficiency and total factor productivity (productivity growth) of the dairy farms in the KwaZulu-Natal Midlands in the last two chapters, the next two chapters deal with environmental efficiency of the dairy farms.

Chapter 8: Econometric estimation of environmental efficiency

8.1 Introduction

The last two chapters dealt with results pertaining to technical efficiency and productivity change over time, and TFP following the Malmquist Index approach for the dairy farms studied in the Midlands of KwaZulu-Natal. Here, the focus shifts to the estimation of the technical and environmental efficiency of a panel of dairy farms in the KwaZulu-Natal Midlands. It was necessary to also re-estimate technical efficiency, because this facilitates better contextualization of environmental efficiency, but this is not the main thrust of the work reported in this chapter. The inclusion of technical efficiency when dealing with environmental efficiency also helps in making comparisons between the two types of efficiency possible.

In this chapter the nitrogen surplus is treated as an environmentally detrimental input[19]. Nitrogen surplus emanates from the application of chemical nitrogenous fertilizer (main source), animal excretion in the form of manure (dung) and urine, and biological and atmospheric fixation in excess of quantities required by plants (for pasture and silage) for their growth and in excess of the soil's nitrogen mineralization capacity (Mkhabela, 2002; Materechera and Mkhabela, 2002; Reinhard *et al*., 1999). Manure can be viewed both as an asset (free organic fertilizer for plant growth) and liability where it is produced in excess of the farm's manure carrying capacity and its disposal is costly (Mkhabela, 2002). Excess nitrogen can escape to the environment (soil, air and water) where it can cause environmental problems through pollution. These environmental problems include: 1) the eutrophication of surface water thus endangering plant and fish life and reducing the aesthetic value of surface water such as lakes and dams; 2) leaching of nitrates into groundwater aquifers; 3) evaporation of ammonia (gaseous form of nitrogen) into the atmosphere, technically known as volatilization, which contributes to acid rain (Reinhard *et al*., 1999).

It is worth keeping in mind that the idea of measuring environmental efficiency in agriculture is not new and considerable work has been done on this topic (for example Hoang and Coelli, 2009; Coelli *et al*., 2007; Roberts *et al*., 2007; Wossink and Denaux, 2006; Färe *et al*., 2005; Reinhard *et al*., 2002; Hadley *et al*., 1999; Chung and Färe, 1995). However, the methods used are varied and evolve rapidly, owing to the difficult of coming up with one method that could be used universally in agriculture. Ball *et al*. (2001) aptly stated that agriculture, unlike most other industries, is diverse; this diversity results in the complexity in measuring environmental efficiency and the need for

[19] The approach of using nitrogen surplus as an environmentally-detrimental input rather than as an environmentally-detrimental output is not new and it has its merits as will be discussed in the methodology section later on. Suffice to say that a number of studies have used this approach. Reinhard *et al*. (1999 and 2000) used nitrogen surplus as an environmentally-detrimental inputs in their analysis of environmental efficiency of a panel of Dutch dairy farms.

unique methods. In this chapter an appropriate methodology for measuring environmental efficiency in the dairy industry will be proposed and applied to the dairy industry in the KwaZulu-Natal Midlands employing the DEA approach.

8.2 Nitrogen pathways in the environment

Nitrogen is an essential element (nutrient) for both plants and animals, and thus indispensable in crop or livestock production. More nitrogen is used in livestock production, such as dairy farming, than in crop production. Given that the dairy farming industry is largely pasture-based in South Africa, nitrogen enters the environment through several sources. One way in which nitrogen is added to the environment is through the application of nitrogenous fertilizer for plant growth (pasture and silage fertilization). Most micro soil nutrients such as phosphorus (P) and potassium (K) are applied to the soil based on soil analysis, thereby ensuring that the correct amount for that particular land is applied as needed by the crop being grown. This is, however, not the case for nitrogen because there is no standard soil nitrogen test that is available to the farming community. Thus nitrogen is applied to the soil regardless of how much nitrogen is already in the system, which often leads to prophylactic application of quantities in excess of plant requirements as farmers generally over-compensate as "insurance". The absence of routine soil tests is due to the high mobility of nitrogen in the soil and the various transformations that nitrogen undergoes in the soil. The mobility of nitrogen, therefore, means that by the time any soil testing results are made available, the nitrogen content of the soil would have changed.

Nitrogen also enters the soil through atmospheric and biological fixation. The farmer has no control over the amount of nitrogen that is deposited in the soil through atmospheric processes such as lightning and general rainfall. Biological fixation is through leguminous and other nitrogen-fixing plant species transforming nitrogen from the air into plant-available nitrogen in the soil through the interaction between their root nodules and bacteria in the soil fauna. The other pathway through which nitrogen is added to the soil and ultimately the greater environment is through animal excreta (faeces and urine). The amount of nitrogen excreted by animals is directly related to the protein[20] content of the feed ingested by the animals. Lastly, nitrogen can be added to the soil system through feed brought on to the farm (concentrates and roughage) and this is particularly important in livestock farming. The points that have been discussed so far are from the input side of the nitrogen cycle as shown in Figure 27.

[20] Nitrogen is a basic constituent of crude protein consisting of about 6.25%.

Figure 27, representing the complete nitrogen cycle, also shows the output side, that is to say, ways in which nitrogen is taken up out of the farming system. In this study, pathways of nitrogen uptake that are considered important are those that form part of sellable or consumable outputs because these eventually leave the farm, thus subtracting nitrogen from the soil. In a system in equilibrium, the quantity of nitrogen applied to the soil should equal the amount used up to satisfy the condition of materials balance (Tyteca, 1995; Coelli *et al.*, 2007). Where nitrogen inputs exceed nitrogen outputs, a condition of surplus nitrogen emissions arises; an undesirable situation as this surplus finds its way into the environment, causing pollution through the contamination of groundwater, rivers and the atmosphere. It is the quantity of nitrogen surplus that is of interest in this chapter and an attempt at quantifying will be done, as discussed later. Figure 27 further shows the transformations that occur to nitrogen in the soil and the various pathways that nitrogen can be lost to the environment. Grey arrows represent nitrogen inputs and black arrows nitrogen outputs. The different forms of nitrogen are represented in bold text and the processes of nitrogen transformation are shown in italics.

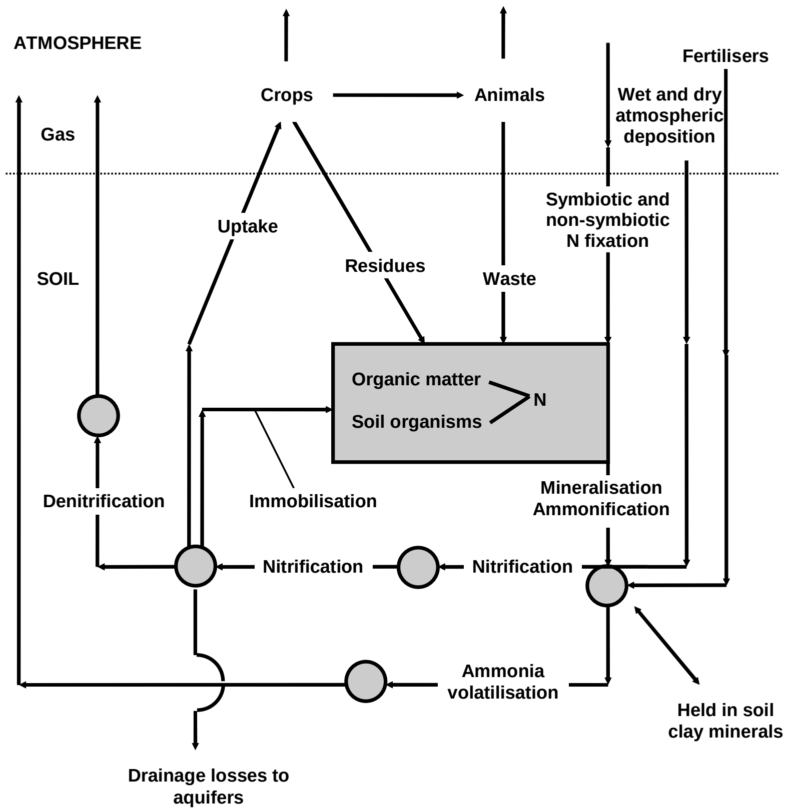


Figure 27: A simplified diagrammatic representation of the nitrogen cycle

Source: Adapted from: Goulding and Poulton (1992)

The illustration in Figure 27 gives a generic representation of the nitrogen cycle in the environment, but a more specific understanding of how nitrogen enters and exits the farm under livestock farming conditions is more enlightening and this is given in Figure 28, which depicts a nitrogen balance accounting system. Here it can be seen that there are mainly four sources of nitrogen that are introduced to the system by the farmer as inputs into the production of saleable goods (the so-called desirables, i.e. pasture, milk, and animals) and the quantities used are within the farmers' control. Some of these desirables are intermediate goods in that they are further used to produce more outputs.

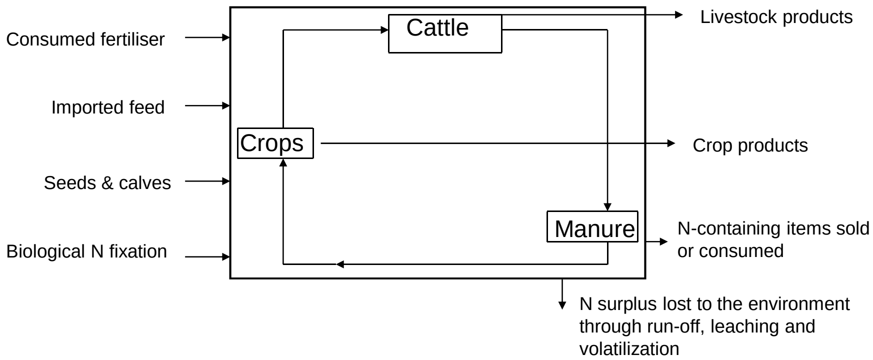


Figure 28: Simplified farm gate method of accounting for the nitrogen balance

Source: Author's own representation

For example, pasture is used as feed to the dairy cows that ultimately produce milk. However, in the process of producing the desirable outputs some by-products of the system have detrimental effects on the larger environment, referred to as undesirables. In the case of dairy farming, cows produce manure and urine (as biological waste products) which contain nitrogen that gets deposited in the soil and leaks into the environment through the pathways shown in Figures 27 to 30. Consumed (used) fertilizer, imported feed, seeds and calves are self-evident as inputs into the production of pastures and milk and only biological nitrogen fixation needs explaining as will be done later on.

The flow of nitrogen from inputs, through products produced to off-takes via nitrogen -containing items sold or consumed shown in Figure 28 will be discussed together with Figure 29, which shows a specific case of nitrogen balance in a closed dairy farm. A "closed" dairy farm refers to a farm where no feed and other nitrogen-containing inputs are imported into the farm, except inorganic fertilizers and seeds.

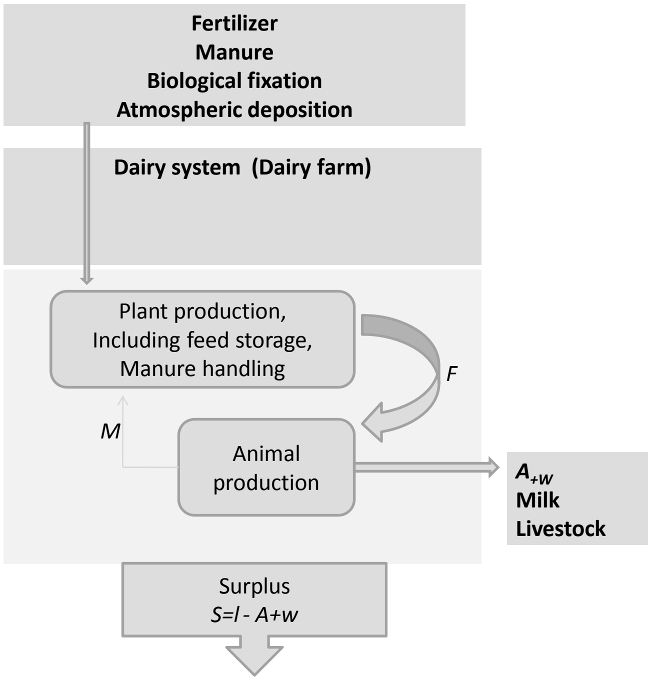


Figure 29: Nitrogen in a closed dairy farm nitrogen system

The top block of Figure 29 shows the basic input sources into this closed dairy farming system (second block), including fertilizer, manure, and nitrogen from both biological fixation and atmospheric deposition. Nitrogen is introduced through both anthropogenic and natural processes in dairy farming. Anthropogenic introduction of nitrogen is through the application of nitrogen fertilizer, manure and the cultivation of legumes and other nitrogen fixing plants in the pasturage system.

Of particular interest is the net value of nitrogen in the system, as a surplus represents more inputs than what the production system requires and this surplus poses a potential threat of 'escaping' the farm into the environment through either leaching into groundwater aquifers, run-off into rivers and other surface water reservoirs in the vicinity in the form of nitrates (NO_2) and nitrites (NO), and/or volatilization into the atmosphere in the form of ammonia (NH_3). The former forms of nitrogen may cause algae bloom in rivers and kill some water life through depleting the water of oxygen, while the latter may lead to acid rain. Nitrous oxide (N_2O), a gas, can also be formed that has been identified as a greenhouse gas contributing to global climate change (Intergovernmental Panel on Climate Change, 2007).

Next, an open dairy farming system is considered as depicted in Figure 30. Although the dairy farming system in the KwaZulu-Natal Midlands is largely pasture-based, it falls within this open system because all dairy farms import some nitrogen containing products, mainly concentrate feed, to boost the protein content of forage. Furthermore, at some stage in the productive life of the farm, animals are brought in as either replacement stock or during expansion of the herd. Figure 30 shows that there is one more source of nitrogen input that has to be considered. Therefore, the nitrogen balance becomes the difference between nitrogen inputs from outside the farm (l off-farm) plus nitrogen input from the farm (l farm) less nitrogen contained in desirable outputs (A_{+W}). In Figure 30 the nitrogen balance is depicted as:

$$S = \left(l_{off-farm} + l_{farm}\right) - A_{+W} \tag{8.1}$$

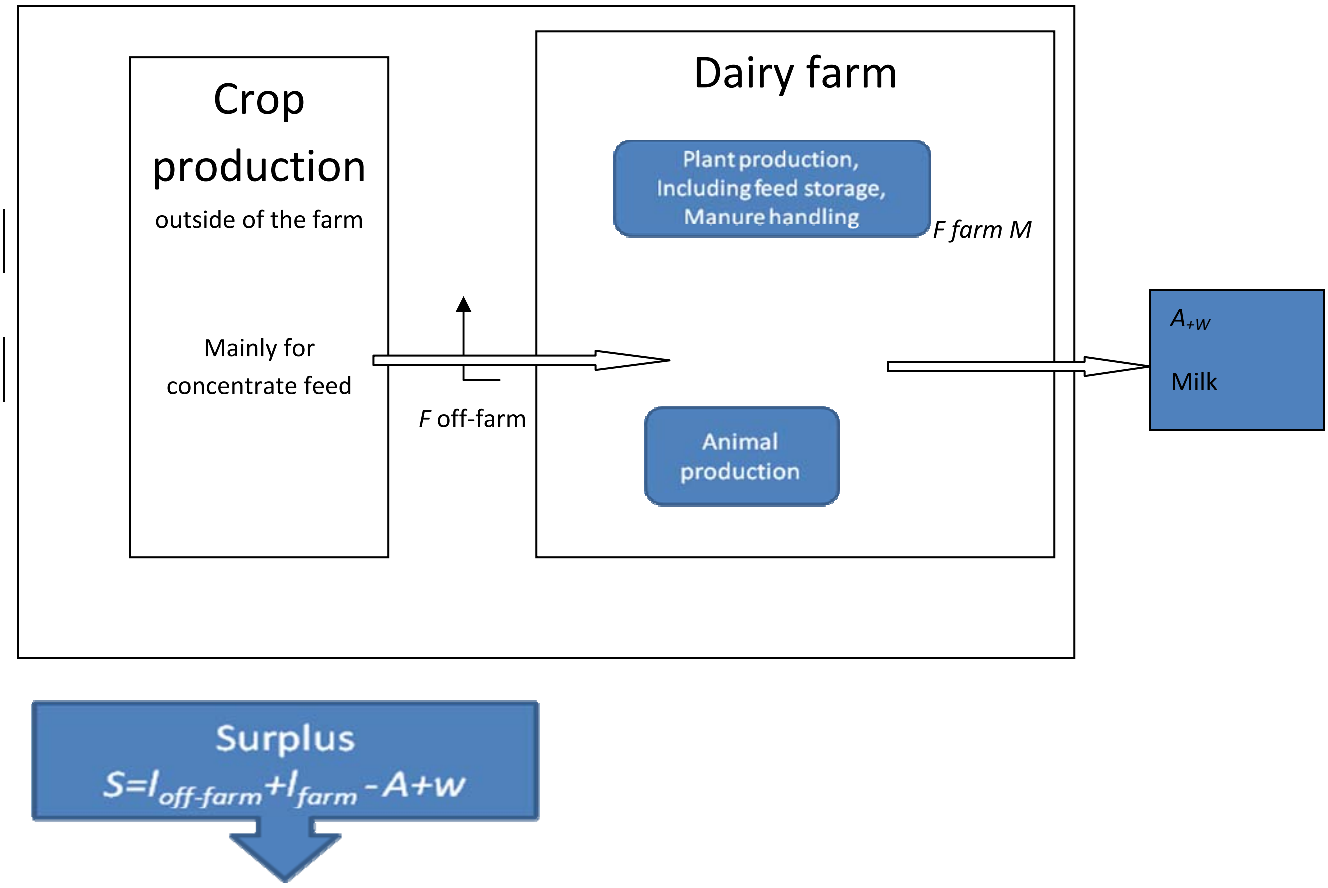


Figure 30: Nitrogen in an open dairy farm nitrogen system

Source: Author's own representation

In South Africa the extent of the environmental problems caused by nitrogen surplus is unknown, and there is no legislation governing the use of nitrogenous fertilizer in farming. However, the absence of any regulatory framework does not preclude the existence of such a problem, nor does it discount the potential of excess nitrogen becoming a serious problem. Given the paucity and/or lack of reported work in the area of the environmental damage caused by a surplus, this study represents pioneering work in South Africa and provides both a theoretical and methodological contribution to the field of efficiency studies.

8.3 Theoretical approaches to econometric estimation of environmental efficiency

A plethora of approaches to measuring environmental efficiency have been proposed and according to Reinhard *et al*. (1999) these can be broadly categorized into two groups namely: 1) those that adjust conventional indexes of productivity change and 2) those which adjust conventional measures of technical efficiency. A common feature of both groups is that the adjustments have focussed on the incorporation of quantifiable environmental effects, often called 'bads' or undesirables, as outputs. Furthermore Reinhard *et al*. (1999: 45) stated that, "…the environmental efficiency indexes can be categorized into those which are calculated using deterministic techniques, which can either be parametric or nonparametric, and those which are estimated using stochastic techniques, which are exclusively parametric." Other approaches to measuring environmental efficiency have looked at incorporating the environmentally detrimental variable as an input in the production system. For example, Cuesta (2000) incorporated the polluting variable (SO_2) as an input in their studies of environmental efficiency measurement of SO_2 emissions from electric utilities in the US with TL distance functions using a parametric approach.

The need to measure environmental efficiency or how to treat the environmentally-detrimental products is necessitated by the fact that production yields multiple outputs using multiple inputs. A particularly significant example of multiple output production involves the simultaneous production of desirable marketed outputs and undesirable, typically non-marketed, by-products such as emissions and pollutants. Because by-products are rarely marketed, they are rarely priced, and so environmental efficiency analysis is frequently based on a primal representation of technology (Cuesta *et al.*, 2009). However conventional distance functions are not well suited for environmental efficiency analysis because they measure performance radially, in terms of the ability to expand all outputs (or contract all inputs) equiproportionally[21]. They do not discriminate between desirable outputs and their undesirable by-products. As Zofío and Prieto (2001:67) remark, output distance functions treat the two sets of outputs symmetrically - a business as usual strategy, while what is required is a distance function that treats desirable and undesirable outputs asymmetrically. The reality that firms often produce multiple outputs that are difficult to aggregate necessitates replacing production functions with distance functions in a primal analysis of producer performance (Cuesta *et al*., 2006 and 2009).

Earlier research taking into account environmental efficiency can be perhaps traced back to 1983. Pittman (1983) was most likely the first to develop an index of productivity change which takes into account environmental efficiency. Pittman (1983) developed a modified Törnqvist productivity index in which environmental effects were treated as additional undesirable outputs which are costly to dispose off. The shortcoming of this approach is that it requires prices for the undesirable outputs, and prices are often unavailable because undesirables are not usually priced on markets. Thus this approach is only feasible where undesirable outputs can be valued by their shadow prices. However, what is required is a distance function that treats desirable and undesirable outputs asymmetrically rather than output distance functions that treat the two sets of outputs symmetrically (Zofío and Prieto, 2001).

In an attempt to address the felt need expressed above Färe *et al.* (1985) introduced such a distance function, a hyperbolic distance function that measures producer performance in terms of the ability to expand outputs and contract inputs equiproportionally. Conventional radial distance functions are oriented toward expanding outputs or contracting inputs, and so are special cases of hyperbolic distance functions. Later on Färe *et al.* (1989) adapted a nonparametric hyperbolic distance function to the measurement of environmental performance. This provided the ability to treat desirable and undesirable outputs asymmetrically, by measuring environmental efficiency in terms of the ability to expand desirable outputs and contract undesirable by-products equiproportionally. A more recent choice when treating outputs and/or inputs asymmetrically can be found in Chambers *et al.* (1996), who introduced an alternative characterization of the production technology by way of the directional distance function. Chung *et al.* (1997) presented the first extension of this distance function for environmental efficiency measurement.

[21] Several authors have attempted to overcome the lack of analytical tools in the parametric field proposing stochastic frontier analysis (SFA). For example Reinhard *et al.* (1999) and Murty & Kumar (2002) used the SFA in their studies. However, these alternatives still do not treat outputs asymmetrically.

8.4 Definition and measurement of environmental efficiency

A definition of technical efficiency has been rendered in the Chapters 6 and 7 and it will suffice here to define environmental efficiency. According to Reinhard *et al*. (1999), environmental efficiency is defined as the ratio of minimum feasible to observed use of an environmentally-detrimental input, conditional on observed levels of the desirable output and conventional inputs. Using the non-radial notion of input efficiency postulated by Kopp (1981), the definition can be expanded to environmental efficiency being an input-oriented, single-factor measure of the technical efficiency of the environmentally detrimental input. The efficiency measure thus defined is the operational definition of environmental efficiency in the study reported in this chapter. This efficiency measure allows for a differential reduction of the inputs applied. The notion of environmental efficiency adopted in this study resonates with models specified by Ball *et al*. (1994) and Tyteca (1997) thus it has been applied effectively by other researchers before and is well documented. It is worth emphasizing that the standard radial, equiproportionate measure of efficiency is insufficiently equipped for identifying the efficiency of individual input use because it treats the contribution of each input to production efficiency equally (Ball *et al*., 1994; Reinhard *et al*., 1999; Tyteca, 1997).

The notion of environmental efficiency is illustrated in Figure 31, which shows a graphical representation of the production frontier in the conventional input and environmentally detrimental input space, while keeping output constant at its observed value, Y_R. A measure of environmental efficiency is provided by the non-radial input-oriented measure

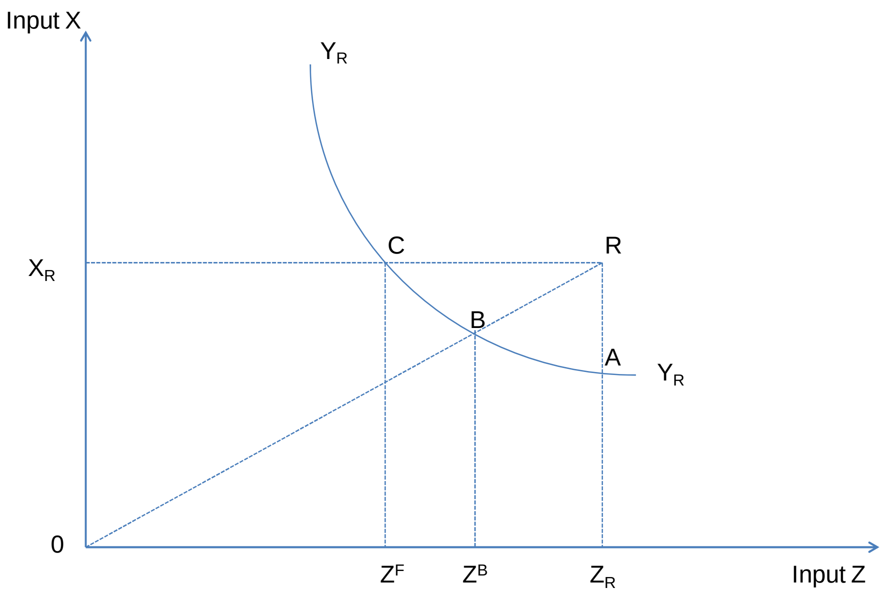


Figure 31: Production frontier in conventional input, X, and environmentally detrimental input, Z, space

Source: Reinhard et al., (1999)

$$
\begin{aligned}
EE_R &= \min\{\theta : F(X_R, \theta Z_R) \geq Y_R\} \\
&= |0Z^F| / |0Z_R|
\end{aligned}
\qquad \textbf{(8.2)}
$$

where Z^F is the minimum feasible environmentally detrimental input use, given $F(\cdot)$ and the observed values of the conventional input X_R and output Y_R. The measurement of technical efficiency using an input-reducing orientation as the ratio of minimum feasible input use to observed input use for a given technology and output level is a radial technical efficiency measure $|0B|/|0R|$. A more comprehensive coverage of the model specification and its attendant derivations is given in Reinhard *et al*. (1999) from whom the analytical approached used in this study is based.

8.5 Estimation of technical and environmental efficiency

Production economics usually treats output as a random variable because of the biological nature of production[22]. Following Coelli (1995) and Reinhard *et al*. (1999), the decision variables are

[22] The level of output in agriculture is largely dependent on weather conditions, outbreak of pests and diseases and other exogenous random factors.

assumed to be fixed in the short run. Therefore relationships in the production system are given by the general specification of the stochastic production frontier:

$$Y_{it} = F(\mathbf{X}_{it}, Z_{it}; \boldsymbol{\beta}) \cdot \exp\{V_{it} - U_i\},$$
$$i = 1,...,I, \qquad t = 1,...,T \tag{8.3}$$

where for all farms indexed with a subscript *i* and for all years indexed with a subscript *t*,

Y_{it} represents the production level;
$\mathbf{X}_{it}$ is a vector of conventional inputs;
Z_{it} is the environmentally detrimental input, nitrogen surplus in this case;
$\boldsymbol{\beta}$ is a technology parameter vector to be estimated;
V_{it} is a random error term, independently and identically distributed as $N(0, \sigma_v^2)$, meant to capture events exogenous to the control of farmers;
U_i is a non-negative random error term, independently and identically distributed as $N^+(\mu, \sigma_u^2)$, intended to capture time-invariant technical inefficiency in production, measured with an output-orientation as the ratio of observed to maximum feasible output.

The stochastic measure of environmental efficiency was favoured in the work report in this chapter over the deterministic measure (to be presented later in Chapter 9) because under the deterministic measure a farm is compared with an efficient farm without any noise, whereas under the stochastic measure a farm is compared to an efficient farm under similar stochastic conditions.

Following the approach of Reinhard *et al.* (1999), the next step is to derive a stochastic environmental efficiency measure from Equation 8.1 by specifying a TL functional form for the deterministic kernel of the stochastic production frontier to give:

$$\begin{aligned}\ln Y_{it} &= \beta_0 + \sum_j \beta_j \ln X_{itj} + \beta_z \ln Z_{it} \\ &+ \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_{itj} \ln X_{itk} \\ &+ \sum_j \beta_{jz} \ln X_{itj} \ln Z_{it} \\ &+ \frac{1}{2}\beta_{zz} (\ln Z_{it})^2 + V_{it} - U_i\end{aligned} \tag{8.4}$$

where $\beta_{jk} = \beta_{kj}$. The logarithm of the output of a technically efficient producer, using X_{it} and Z_{it} to produce Y_{it}^F, is obtained by setting $U_i = 0$. Whereas the logarithm of an environmentally efficient producer, using X_{it} and Z_{it}^F to produce Y_{it}, is obtained by replacing Z_{it} with Z_{it}^F and setting $U_i = 0$ in Equation 8.3 to obtain:

$$\begin{aligned} \ln Y_{it} &= \beta_0 + \sum_j \beta_j \ln X_{itj} + \beta_z \ln Z_{it}^F \\ &+ \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_{itj} \ln X_{itk} \\ &+ \sum_j \beta_{jz} \ln X_{itj} \ln Z_{it}^{F'} \\ &+ \frac{1}{2}\beta_{zz}(\ln Z_{it})^2 + V_{it} \cdot \end{aligned} \quad \textbf{(8.5)}$$

The stochastic environmental efficiency logarithm ($\ln EE_{it} = \ln Z_{it}^F - \ln Z_{it}$), can be further isolated by setting Equations 8.3 and 8.4:

$$\begin{aligned} &\frac{1}{2}\beta_{zz}\left[(\ln Z_{it}^F)^2 - (\ln Z_{it})^2\right] \\ &+ \sum_j \beta_{jz} \ln X_{itj}\left[\ln Z_{it}^F - \ln Z_{it}\right] \\ &+ \beta_z\left[\ln Z_{it}^F - \ln Z_{it}\right] + U_i = 0 \end{aligned} \quad \textbf{(8.6)}$$

And this can be rewritten as:

$$\begin{aligned} &\frac{1}{2}\beta_{zz}\left[\ln Z_{it}^F - \ln Z_{it}\right]^2 \\ &+ \left[\beta_z + \sum_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it}\right] \\ &\mathrm{x}\left(\ln \mathrm{Z}_{\mathrm{it}}^{\mathrm{F}} - \ln Z_{it}\right) + U_i = 0 \end{aligned} \quad \textbf{(8.7)}$$

Equation 8.6 can be solved for $\ln EE_i = \ln Z_{it}^F - \ln Z_{it}$ to yield:

$$\ln EE_i = \left[-\left(\beta_z + \sum_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it} \right) \right.$$
$$\pm \left\{ \left(\beta_z + \sum_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it} \right)^2 \right. \qquad \textbf{(8.8)}$$
$$\left. \left. - 2\beta_{zz} U_i \right\}^5 \right] / \beta_{zz}$$

The environmental efficiency is calculated using the square root (+√ formula) of Equation 8.8

8.6 Data

The data used in this study are production data for 37 dairy farms in the KwaZulu-Natal Midlands in South Africa as described earlier (Sections 4.3 to 4.5). However, it is necessary to discuss the nitrogen surplus data which has not been used in previous chapters. The dataset did not contain any explicit quantitative nitrogen input into the production system (such as quantities of nitrogen fertilizer, nitrogen-containing feedstuff like concentrates and imported silage and hay, manure applied to the soil for plant growth). By the same token, no quantitative information on nitrogen outputs, either in saleable products (milk, silage, and meat) or nitrogen surplus in the form of manure produced and nitrogen in excess of what was converted into marketable products was available. The lack of data on nitrogen surplus necessitated estimation of nitrogen surplus following the method suggested by the OECD (2001) for soil surface nitrogen balances and further used by Roberts *et al*. (2007). This methodology of estimating nitrogen surplus takes into account the nitrogen content of animal excretion (urine and dung); of milk and meat products; of grass (pasture) and of maize for silage on the output side. On the input side it takes into consideration the amount of nitrogen applied to soil through fertilizer and manure application, both biological and atmospheric fixation of nitrogen. The nitrogen surplus (deficit) is therefore the difference between nitrogen applied to nitrogen remaining in the farming system and not taken up into marketable products. The nitrogen surplus is susceptible to being lost into the environment, causing pollution problems discussed in the introductory section of this chapter.

Before the data were used for efficiency measurement, the data were converted into a per hectare basis to minimize the likelihood of multicollinearity by taking out the effect of farm size, as the N surplus is undoubtedly closely related to land size. Table 52 shows the summary of the sample variables, where it can be observed that farms in the sample were highly varied. For example, in terms of output in Rand value, the highest output was over R819 000 while the lowest was around

R47 000, with an average of R267 000. The feed variable was another variable that exhibited substantial variation between farms. One farm incurred a feed bill in excess of R1.165 million and another farm at the lower end of the scale incurred a feed bill of just over R18 000 on average. The mean feed cost for the sample was R166 288. Of particular interest to this chapter is the nitrogen surplus variable, which was distributed around the mean of 350.5 kg/ha with a standard deviation of 26.6 kg/ha. The farm with the highest nitrogen surplus had 416.9 kg/ha while the lowest was 278.8 kg/ha.

Table 50: Summary of sample variables for the dairy farms

Variable	Maximum	Mean	Minimum	Std. Dev.
Output (R)	819 182	266 529	46 943	138 658
Land (hectares)	455	205	84	76
Labour (full-time equivalent)	52	21	10	7
Labour (R)	75 588	23 704	1 049	11 932
Feed (R)	1 165 930	166 288	18 346	149 515
Veterinary services (R)	260 001	31 561	2 134	40 728
Other machinery (R)	397 164	37 781	683	57 958
Milking machinery (R)	218 579	24 559	454	35 556
Herd size	669	289	149	103
Nitrogen surplus ($kgha^{-1}$ N)	416.9	350.5	278.8	26.6

8.7 Results

Technical efficiency of each farm is assumed to be constant during the study period and is allowed to follow a truncated normal distribution. The time-invariant specification was adopted; this was considered reasonable because there are a maximum of eight observations per farm, a minimum of five and an average of 6.9. A likelihood-ratio test of the hypodissertation that inefficiency is absent is rejected, with a test statistic of 67.349668. The point estimate of $\sigma_u/(\sigma_u/\sigma_v)$ implies that 58% (57.99%) of the residual is due to inefficiency.

Two different models were estimated to tackle the issue of choice of the functional form for the production function, which is done by testing the adequacy of the restrictive CD against the more flexible TL model. The CD model was rejected outright as it does not allow for the estimation of efficiency. The models estimated and reported were: 1) a TL time-invariant model on mean-differenced per hectare data and 2) a TL time-invariant inefficiency model on non-mean differenced per hectare data. The concept of mean differencing was discussed in detail in Chapter 4. It is useful to look at the structure of the estimated production technology before discussing the technical and environmental efficiency results.

The results of the TL mean-differenced inefficiency model are discussed first as reported in Table 53. The estimated coefficients (which are the elasticities) of output for each input were evaluated at the entire sample level. It should be noticed that time is included as one of the inputs in order to take into account any technological and policy changes that may have occurred during the years of the study. The elasticity of time is positive for the farms in the sample, albeit very small. Another observation warranting discussion is that the elasticities of output with regard to the other five inputs (land; labour; feed; veterinary services and medicines; and nitrogen surplus), excluding time, were all positive and significant. Labour had the highest coefficient (0.28) implying that an increase in the use of labour by 1% would lead to an increase in output of 0.28%. Labour was followed by feed with an elasticity of 0.13. Veterinary costs, milking machinery and other machinery all had elasticities less than 0.1 of around 0.05, signalling relatively small positive contributions to output. The gamma statistics in Table 53 is $\sigma_u/(\sigma_{u+}\sigma_{v})$ is a measure of whether the data, and the analysis thereof, is a TL or frontier. The gamma value (0.76) in Table 53, which is significant at the 5 percent level, shows that it is a frontier.

Given that the work reported in this chapter is largely concerned with the environmental efficiency of the farms, it is particularly pertinent to scrutinize the estimated elasticities of output of the nitrogen surplus input. The output elasticity of nitrogen surplus was -0.715 with a standard error of 0.179, implying that a one percent reduction in nitrogen surplus would lead to a 0.7% increase in output (milk and other marketable products such as silage and meat), *ceteris paribus*. This is an interesting finding in that generally a reduction in input use leads to a decrease in output but in this case the reverse is true. This could further imply that the farmers are over-utilizing nitrogen fertilizer which is known to lead to luxury consumption of nitrogen by plants, which in turn, may lead to a reduction in milk production as a result of hypoglycaemia in cows. Miles and Hardy (1999) stated that on average most dairy farmers in the KwaZulu-Natal Midlands applied more nitrogen fertilizers on pastures than was required. Miles and Hardy (1999) ascribed the over-application of nitrogen fertilizers to the fact that there is no standard routine soil testing method for nitrogen to facilitate accurate fertilizer recommendations, owing to the elusive nature of the nitrogen element. Nitrogen is highly mobile in the soil, undergoing numerous transformations thus making it difficult to know how much nitrogen is in the soil at any given time (Materechera and Mkhabela, 2002).

Table 51: Parameter estimates (translog mean differenced time-invariant model)

Variable	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Labour (l)	0.281973**	0.044368	6.36	0	0.195015	0.368932
Feed (f)	0.129691*	0.030159	4.3	0	0.070581	0.188801
Veterinary cost (v)	0.047692	0.014674	3.25	0.001	0.018931	0.076454
Milk machinery (mm)	0.048148	0.018047	2.67	0.008	0.012776	0.08352
Other machinery (om)	0.055577	0.020479	2.71	0.007	0.01544	0.095714
Nitrogen surplus (n)	-0.71493	0.178945	-4	0	-1.06566	-0.36421
ll	-0.02151	0.044153	-0.49	0.626	-0.10805	0.065023
ff	0.018883	0.010818	1.75	0.081	-0.00232	0.040086
vv	-0.02967	0.011065	-2.68	0.007	-0.05136	-0.00799
mmmm	-0.02496	0.013407	-1.86	0.063	-0.05124	0.001319
omom	0.011293	0.013744	0.82	0.411	-0.01564	0.03823
nn	0.565405	0.683248	0.83	0.408	-0.77374	1.904545
lf	0.111661	0.066056	1.69	0.091	-0.01781	0.241128
lv	0.023116	0.042202	0.55	0.584	-0.0596	0.105831
lmm	-0.00482	0.049573	-0.1	0.923	-0.10198	0.092343
lom	-0.00948	0.073502	-0.13	0.897	-0.15354	0.134582
ln	-0.30796	0.309369	-1	0.32	-0.91431	0.298395
fv	0.040592	0.032441	1.25	0.211	-0.02299	0.104174
fmm	-0.09631	0.027871	-3.46	0.001	-0.15093	-0.04168
fom	0.081601	0.046799	1.74	0.081	-0.01012	0.173326
fn	0.273214	0.260584	1.05	0.294	-0.23752	0.783949
vmm	0.030952	0.017063	1.81	0.07	-0.00249	0.064396
vom	-0.00923	0.022873	-0.4	0.687	-0.05406	0.035602
vn	0.093194	0.109146	0.85	0.393	-0.12073	0.307117
mmom	-0.02052	0.023669	-0.87	0.386	-0.06691	0.025874
mmn	0.15911	0.149293	1.07	0.287	-0.1335	0.451718
omn	0.196313	0.198469	0.99	0.323	-0.19268	0.585305
_cons	0.405868	0.06063	6.69	0	0.287035	0.524702
/mu	0.346633	0.119012	2.91	0.004	0.113374	0.579891
/lnsigma2	-2.32911	0.336929	-6.91	0	-2.98948	-1.66874
/ilgtgamma	1.158674	0.458097	2.53	0.011	0.260821	2.056528
sigma2	0.097382	0.032811			0.050314	0.188484
gamma $\sigma_u/(\sigma_u+\sigma_v)$	0.761092**	0.083296			0.564838	0.886606
sigma_u2	0.074117	0.032845			0.009741	0.138492
sigma_v2	0.023265	0.002238			0.018879	0.027652
**Significant at 5% level; *significant at 10% level						

Lastly, the sample exhibited the existence of decreasing returns to scale as indicated by the sum of the five elasticities of 0.93. The time variable was excluded because it is widely accepted that the summation of the output elasticities of the conventional inputs is an alternative measure of returns to scale (Reinhard *et al*., 1999, 2000; Cuesta *et al*., 2009).

The nitrogen surplus results implicate the finding made earlier that it seems that farmers in the area of study are over-using nitrogen and they can actually reduce the nitrogen application without losing out on output and also save money by buying less nitrogen fertilizer. Reducing the fertiliser input will actually reduce the bad output (nitrogen surplus) and increase the good output (milk). A logical explanation of this finding could be that the soils in the KwaZulu-Natal Midlands are well-weathered (old soils), deep and have a high clay content which gives them a high nitrogen mineralization capacity (Mkhabela, 2002). Given the nature of the soils and the long history of nitrogen application, it is not unreasonable to expect the soils to have high inherent nitrogen content and this has been shown to be true (Mkhabela, 2002).

Having discussed the production function under the flexible TL inefficiency model and the elasticities of the various input variables, the following section is dedicated to discussing the technical and environmental efficiency of the farms. In order to get farm level efficiencies, technical efficiency coefficients were applied to the original data because the application of technical efficiency coefficients makes the inefficiency terms (Zs) differ by farm. Table 54 reports the estimates of technical efficiency of the dairy farms for each farm per year. Included in Table 54 is the percentage change in technical efficiency over the years; this change is based on the first (2000) and last (2007) years and the applicable starting and ending year vary from farm to farm given that the dataset used is an unbalanced panel. For example, Farms 1 to 6 only start in 2002, while farms 8 to 16, as well as 20 and 21 end in 2006.

In 2000 there were only 25 farms in the sample and the average technical efficiency score was 0.66 with a range of 0.41 to 0.93. Farm 17 recorded the lowest technical efficiency of 0.41, and farms 33 and 34 had the highest efficiency scores of 0.93. A closer look at Farm 17 reveals that this farm was relatively small with 188 cows, but had a high labour complement of 20 workers and paid one of the lowest wages of less R1 000 per month. These indications point towards the farm's inappropriate allocation of resources (low stocking rate) and employing low quality labour since labour wages were used a proxy of labour quality (see Chapter 4 for a comprehensive discussion of the variables). Looking at farms 33 and 34, the best performers in terms of technical efficiency reveals that these farms had high incomes from milk sales of more than R285 000 and R284 000 in year 2000, putting them among the highest earners.

What is more interesting, however, is that these two farms were of similar size, in terms of land, to farm 17 indicating that they were able to generate more output per given unit of land thus rendering them more technically efficient. The trend continued throughout the eight years under review with Farm 17 consistently under-performing and Farms 33 and 34 consistently being the closest to efficiency with an efficiency score of 0.93.

Table 52: Estimates of technical efficiency for the dairy farms from 2000 to 2007

Farm	2000	2001	2002	2003	2004	2005	2006	2007	%change
1	-	-	0.66	0.66	0.66	0.66	0.66	0.67	0.93
2	-	-	0.58	0.58	0.58	0.59	0.59	0.59	1.22
3	-	-	0.60	0.60	0.60	0.61	0.61	0.61	1.14
4	-	-	0.44	0.44	0.45	0.45	0.45	-	1.47
5	-	-	0.52	0.52	0.52	0.53	0.53	-	1.18
6	-	-	0.86	0.86	0.86	0.87	0.87	-	0.26
7	0.62	0.62	0.63	0.63	0.63	0.63	0.63	0.63	1.27
8	0.61	0.61	0.61	0.61	0.62	0.62	0.62	-	1.33
9	0.62	0.62	0.62	0.62	0.62	0.62	0.63	-	1.29
10	-	-	0.58	0.58	0.58	0.58	0.59	-	0.98
11	-	-	0.68	0.68	0.68	0.68	0.69	-	0.69
12	0.76	0.76	0.76	0.76	0.76	0.76	0.76	-	0.75
13	-	-	0.76	0.76	0.76	0.76	0.76	-	0.50
14	-	-	0.73	0.73	0.73	0.73	0.73	-	0.57
15	0.58	0.58	0.58	0.58	0.58	0.58	0.59	-	1.48
16	0.87	0.87	0.87	0.87	0.87	0.88	0.88	-	0.36
17	0.41	0.41	0.41	0.41	0.41	0.42	0.42	0.42	2.84
18	-	-	0.40	0.41	0.41	0.41	0.41	0.41	1.64
19	-	-	0.52	0.52	0.52	0.52	0.52	0.52	1.19
20	0.70	0.70	0.70	0.70	0.71	0.71	0.71	-	0.95
21	0.59	0.59	0.59	0.59	0.59	0.59	0.60	-	1.44
22	0.57	0.57	0.58	0.58	0.58	0.58	-	-	1.25
23	0.56	0.56	0.56	0.56	0.56	0.57	0.57	0.57	1.83
24	0.68	0.68	0.68	0.68	0.68	0.69	0.69	0.69	1.21
25	0.56	0.57	0.57	0.57	0.57	0.57	0.57	0.58	1.79
26	0.66	0.67	0.67	0.67	0.67	0.67	0.67	0.67	1.28
27	0.74	0.74	0.74	0.74	0.74	0.75	0.75	0.75	0.94
28	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	1.22
29	0.52	0.52	0.52	0.52	0.52	0.52	0.53	0.53	2.08
30	0.54	0.55	0.55	0.55	0.55	0.55	0.55	0.55	1.91
31	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.95
32	0.60	0.60	0.60	0.60	0.61	0.61	0.61	0.61	1.60
33	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.23
34	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.24
35	0.70	0.70	0.70	0.70	0.70	0.70	0.71	0.71	1.12
36	0.65	0.65	0.65	0.65	0.65	0.65	0.66	0.66	1.36
37	0.75	0.75	0.75	0.76	0.76	0.76	0.76	0.76	0.89
mean	**0.66**	**0.66**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**1.17**
min	**0.40**	**0.41**	**0.40**	**0.41**	**0.41**	**0.41**	**0.41**	**0.41**	**0.23**
max	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**	**2.84**

Lastly, looking at the percentage change in efficiency over the years per farm shows minimal increases of between 0.23 to 2.84%. Percent change was calculated as an average percent change over the entire period. That is, the percent change from year to year was calculated, added together and them divided by the number of years. What is more interesting is the identity of the farms with the lowest and highest improvement. Farm 17, the least efficient farm, posted the highest percentage change in technical efficiency indicating a high degree of 'learning' and improvement over the years while Farm 33, one of the two most efficient farms in the sample, posted the lowest percentage change of merely 0.23, probably implying a degree of complacence or having reached its capacity for technical efficiency improvements. Overall, there was a 3.09% increase in the minimum technical efficiency, a negligible decline in the maximum efficiency of -0.07% and overall increase in the mean technical efficiency of 2.38%. The technical efficiency of each farm did not vary much throughout the years for which data were available, further lending credence to the view that technical efficiency was time-invariant for dairy farms in the KwaZulu-Natal Midlands.

Moving on to the environmental efficiency of farms in the sample, an interesting picture emerges as shown in Table 55. For most of the farms, environmental efficiency was consistently higher than their technical efficiency, which was somewhat unexpected yet not illogical because farms could be technically more efficient at the expense of environmental efficiency and vice versa. This finding seems to suggest that technical efficiency and environmental efficiency are not necessary mutually exclusive. The lowest environmental efficiency score of 0.65 was much higher than the lowest technical efficiency score of 0.40, although the highest environmental efficiency score of 0.81 was substantially lower than the highest technical efficiency score of 0.93. Unlike technical efficiency, there were considerable gains in environmental efficiency for the farms. The sample mean environmental efficiency grew from 0.76 to 0.78 representing a 2.35% growth. The minimum (least environmentally-efficient farm) showed the highest improvement of 17.48%, growing from 0.65 in 2000 to 0.76 in 2007. However, the maximum did not improve much as only a 2.35% growth was realised, growing from 0.79 to 0.81. The results show that the largest gains were made by farms that started quite low in their environmental efficiency as opposed to those that were already relatively more environmentally-efficient.

Table 56 reports the rankings of farms according to estimates of technical efficiency and the calculated[23] environmental efficiency of the dairy farms. The estimates of technical efficiency were moderately high and remained constant at around 0.65 throughout the eight years (2000 to 2007) of study. The constant technical efficiency levels of the farms lend credibility to the assertion made earlier that the sample data exhibited time invariant (in)efficiency. However, given that technical efficiency was modelled as time-invariant, the slight variation in annual means is due to changes in the composition of the farms that made up the sample each year as farms enter and exit the sample, as Reinhard *et al*. (1999) observed in their study of the Dutch dairy industry. The moderate levels of technical efficiency give ambivalent suggestions. On the one hand, these could suggest that the substantial marketable output is foregone due to resource waste because the point of diminishing returns for nitrogen fertilizer has been reached. On the other hand, the moderate levels of technical

[23] It should be noted that the environmental efficiency levels were actually calculated and not estimated following the procedure outlined in Equation 8.7.

efficiency could imply underutilized capacity. The sample also showed substantial differences in their technical efficiency levels as indicated by the differences between the minimum value of 0.40 and the maximum of 0.93.

Table 53: Estimates of environmental efficiency for the dairy farms from 2000 to 2007

Farm	2000	2001	2002	2003	2004	2005	2006	2007	%change
1	-	-	0.77	0.78	0.77	0.76	0.79	0.78	1.13
2	-	-	0.77	0.76	0.77	0.78	0.78	0.79	2.59
3	-	-	0.75	0.77	0.76	0.76	0.75	0.77	2.42
4	-	-	0.75	0.75	0.76	0.76	0.76	-	0.99
5	-	-	0.76	0.77	0.74	0.75	0.75	-	-1.08
6	-	-	0.73	0.74	0.73	0.76	0.75	-	2.64
7	0.79	0.79	0.79	0.80	0.79	0.79	0.78	0.80	1.75
8	0.76	0.75	0.76	0.79	0.77	0.73	0.77	-	2.06
9	0.76	0.76	0.78	0.78	0.78	0.77	0.78	-	2.20
10	-	-	0.75	0.75	0.76	0.76	0.77	-	2.40
11	-	-	0.75	0.76	0.77	0.76	0.77	-	2.01
12	0.78	0.76	0.75	0.73	0.73	0.74	0.74	-	-5.58
13	-	-	0.76	0.74	0.75	0.77	0.77	-	0.86
14	-	-	0.76	0.76	0.76	0.76	0.76	-	0.20
15	0.77	0.77	0.76	0.75	0.78	0.77	0.77	-	-0.15
16	0.74	0.76	0.76	0.78	0.78	0.78	0.77	-	5.11
17	0.77	0.78	0.78	0.76	0.76	0.76	0.76	0.77	-1.76
18	-	-	0.78	0.76	0.77	0.79	0.79	0.79	0.59
19	-	-	0.78	0.78	0.78	0.80	0.79	0.79	0.82
20	0.75	0.72	0.71	0.74	0.74	0.75	0.74	-	-0.36
21	0.77	0.76	0.76	0.79	0.80	0.80	0.81	-	5.24
22	0.78	0.78	0.79	0.79	0.78	0.80		-	1.49
23	0.76	0.80	0.79	0.79	0.79	0.79	0.78	0.79	3.91
24	0.76	0.77	0.77	0.78	0.79	0.78	0.79	0.79	3.83
25	0.75	0.73	0.74	0.71	0.75	0.76	0.76	0.77	1.98
26	0.76	0.75	0.75	0.75	0.75	0.77	0.76	0.76	0.37
27	0.73	0.74	0.65	0.75	0.76	0.76	0.76	0.76	3.99
28	0.73	0.74	0.74	0.75	0.76	0.77	0.76	0.76	3.61
29	0.75	0.75	0.75	0.77	0.77	0.77	0.77	0.77	3.45
30	0.75	0.75	0.75	0.76	0.76	0.77	0.76	0.77	2.33
31	0.77	0.77	0.79	0.74	0.79	0.76	0.77	0.81	4.35
32	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.80	3.73
33	0.77	0.79	0.81	0.77	0.77	0.77	0.78	0.77	-0.91
34	0.77	0.79	0.81	0.77	0.77	0.78	0.78	0.78	1.65
35	0.77	0.77	0.78	0.77	0.77	0.77	0.78	0.78	1.64
36	0.77	0.76	0.79	0.79	0.80	0.79	0.79	0.79	1.90
37	0.78	0.77	0.78	0.79	0.79	0.80	0.81	0.79	1.27
mean	**0.76**	**0.76**	**0.76**	**0.77**	**0.77**	**0.77**	**0.77**	**0.78**	**2.35**
min	**0.65**	**0.71**	**0.73**	**0.73**	**0.74**	**0.76**	**0.74**	**0.76**	**17.48**
max	**0.79**	**0.80**	**0.81**	**0.80**	**0.80**	**0.80**	**0.81**	**0.81**	**2.38**

Interestingly, the environmental efficiency was substantially higher than technical efficiency and exhibited less variability than technical efficiency with a range of 0.65 to 0.85 and a mean of 0.77.

The environmental results are interesting because they are different from those of other similar studies done elsewhere. For example, Reinhard *et al*. (1999) in their study of the Dutch dairy industry and Baltussen *et al*. (1992), also in The Netherlands, found that environmental efficiency was much lower on average and exhibited much greater variability than technical efficiency. The relatively high average environmental efficiency and low variability could be partly explained by the small differences in nitrogen surplus between farms with similar production levels per hectare. The other explanation could have something to do with the extensive nature of dairy farming in the KwaZulu-Natal Midlands as opposed to the intensive production systems of The Netherlands, for example. Similar to technical efficiency, environmental efficiency also remained fairly constant during the years of the study at around an annual mean of 0.77.

The study would be incomplete without giving attention to the relationship (compatibility or lack of) between technical efficiency and environmental efficiency. An interesting question is: Does improvement in technical efficiency lead to an increase in environmental efficiency or are the two mutually exclusive? The following analyses, emanating from the results reported in Tables 57 and 58 will shed light on this question as the rankings reported in Table 56 are analysed. Table 57 shows the 37 dairy farms ranked according to their technical and environmental efficiency and Table 58 shows the correlation between technical and environmental efficiency using Spearman and Ktau correlations. In considering the compatibility of the two types of efficiency, it can be observed upfront that farms rank differently according to technical efficiency and environmental efficiency. It is commonly accepted that technical efficiency is necessary for environmental efficiency (see Reinhard *et al*., 1999, for example). The results reported in Table 58 cast doubt on whether technical efficiency is a necessary and sufficient precondition for environmental efficiency. Looking at these results, it appears that there is a trade-off between technical efficiency and environmental efficiency as there appears to be dissonance between the two types of efficiency. In short, the apparent contraction shows that the two rankings are not related. The divergence between the rankings is remarkable as few farms appear in the same quartile for both technical and environmental efficiency. The Spearman rank correlation (Spearman rho) between the two measures was 0.0367 as indicated in Table 58 and the probability for the test of Ho: technical efficiency and environmental efficiency are independent was 0.8290. A further correlation test was conducted using the Ktau approach which is suited to small samples (StataCorp, 2009) and the results were similar to the Spearman rank correlation but more pronounced.

Table 56: Ranking of dairy farms by technical and environmental efficiency

Rank	Farm number	
	Technical efficiency	Environmental efficiency
1	34	7
2	35	37
3	17	19
4	6	22
5	14	23
6	13	36
7	28	21
8	32	34
9	15	18
10	21	24
11	36	33
12	25	31
13	12	1
14	29	2
15	27	35
16	1	32
17	37	9
18	7	17
19	10	16
20	8	15
21	9	29
22	33	11
23	2	8
24	3	3
25	22	14
26	11	30
27	16	13
28	23	10
29	26	26
30	24	4
31	31	5
32	5	28
33	30	12
34	20	25
35	4	6
36	18	27
37	19	20

Table 57: Spearman correlation of technical and environmental efficiency

	TE	EE
TE	1.0000	
EE	0.0367	1.0000
Number of observation = 37		
Spearman's rho = 0.0367		
Prob > |t| = 0.8290		
Test of Ho: technical efficiency and environmental efficiency are independent		

The Ktau rank correlation was 0.018 and the probability that technical efficiency and environmental efficiency are independent was 0.8856. The largest drop in ranking between technical efficiency and environmental efficiency was 25 places for Farm 28, which was ranked 7th for technical efficiency and 32nd for environmental efficiency, with the smallest seven places for Farm 34 (ranked first for technical efficiency and 8th for environmental efficiency).

Table 58: Ktau correlation of technical and environmental efficiency

Number of observation	37
Kendall's tau-a	0.0180
Kendall's tau-b	0.0180
Kendall's score	12
SE of score	76.459
Prob > |z|	0.8856
Test of Ho: technical efficiency and environmental efficiency are independent	

8.7 Summary

Environmental efficiency was calculated as a single-factor measure of input-oriented technical efficiency. Furthermore, it was shown in this study how environmental efficiency can be estimated within a stochastic TL production frontier. The main finding was that less nitrogen increases both environmental and technical efficiency. This is because for these farms, on average, the soils in the area where they are located have high inherent fertility and high nitrogen mineralization potentials and thus do not require as much nitrogen fertiliser as is currently applied. It was found that the dairy farms in the Midlands of KwaZulu-Natal achieved relatively low technical efficiency, 0.66 on average. It was, however, found in this study that the dairy farms achieved generally higher levels of environmental efficiency (0.77 on average, with the best achieving 0.85). Lastly, the results showed that technical efficiency and environmental efficiency were independent for the farms in the sample, meaning that the fertiliser efficiency is not sufficient to give a positive correlation between the two efficiencies – the other variables dominate the relationship.

In the following chapter (Chapter 9) the environmental efficiency results of 34 dairy farms participating in a pasture-utilization study are reported, following the nonparametric mathematical DEA approach. Given that the elasticities for the nitrogen surplus variable reported in this chapter (Chapter 8) vary across farms and that the DEA is more accurate in the sense that the coefficients (elasticities) are calculated rather than estimated, it was deemed necessary to also analyse environmental efficiency using the DEA approach.

Chapter 9: Nonparametric calculation of environmental efficiency

9.1 Introduction

Chapter 7 reported the results of efficiency and total factor productivity growth of the farms using the DEA approach. The previous chapter (Chapter 8) analysed environmental efficiency of the farms following the parametric mathematical stochastic frontier approach (SFA). The results reported in this chapter are for environmental efficiency of the dairy farms, measured in terms of efficiencies in the utilization of nitrogen as indicated by surplus nitrogen production. Nitrogen surplus is the difference between the applied nitrogen plus the nitrogen contained in marketable products and the nitrogen that remains on the farm (excess nitrogen that was not used in the production of the desirable outputs – milk, pasture and meat products).

9.2 A brief review of environmental extension of DEA

The complications introduced to efficiency analysis by trying to incorporate environmental efficiency have already been discussed. The efficiency level of any decision making unit, a farm in this particular study, measured via the DEA is defined by its input and output quantities, where more output from less inputs, other things being constant, gives a higher degree of efficiency (Dyckhoff and Allen, 2001). So, the basic DEA approach assumes that inputs and outputs are desirable. However, such assumption loses validity when environmental efficiency is considered because environmental efficiency by definition is concerned with either the use or production of environmentally undesirable input(s) or output(s), respectively.

There has been considerable work done in measuring efficiency using the DEA approach, and a number of studies have looked at incorporating some environmental efficiency aspects. Allen (1999) carried out a review of 29 studies using the DEA to measure efficiency and found that 17 of the 29 reviewed incorporated environmental efficiency, although Allen (1999) referred to this environmental efficiency as ecological efficiency.

9.3 The proposed approach

Initially the data for 37 farms from 2000 to 2007 was used to calculate environmental efficiency using DEA, as was done for technical efficiency in Chapter 6, in order to stick to the tried and tested model. However, this approach was abandoned, because the results gave unreasonable environmental efficiencies of close to unitary (signifying full environmental efficiency) for all the farms. Next was to try and use similar input variables as used in Chapter 6, but with the cross-sectional data for only 34 farms participating in a pasture utilization improvement study group with good nitrogen data. But this also did not work well: the data set was not sufficiently large. The last resort was to use the more nitrogen related data (quantities of nitrogen applied by each farm, quantities of nitrogen containing feed imported on to the farm in concentrates and purchased silage, etc). This gave better results, albeit at the cost of model misspecification; this approach was adopted following Dyckhoff and Allen (2001) and Allen (1999).

Given that DEA looks at the quantity of output versus input use, in other words the DEA measures efficiency as the ability of converting inputs into output, it was necessary to manipulate the data, particularly the nitrogen surplus quantities. In order for DEA to correctly analyze environmental efficiency, the nitrogen surplus values were inverted, that is the inverse of the values were used. Using the inverse facilitates identifying farms with high N surplus values being less environmentally benign, thus less environmentally efficient, and those farms with low N surplus values as being more environmentally efficient (taking into consideration the use of inputs, especially N fertilizer and feed concentrates). This approach of taking the reciprocal of the nitrogen surplus has been used successfully before in other studies (for example, Dyckhoff and Allen, 2001).

Production technology

Before introducing the proposed analytical approach it would suffice to give a brief discussion of a production system that incorporates a polluting or an environmentally-detrimental output.

A production process in which aggregate fertilizer consumption (F), output – milk and other product (Y) and nitrogen surplus (N) are respectively taken as input, desirable output, and undesirable output is considered. The production technology can be described as:

$$T = \{(F, Y, N) : \text{F can produce } (Y, N)\} \quad \textbf{(9.1)}$$

Note that a finite amount of input can only produce finite amounts of outputs as T is often assumed to be a closed and bounded set in production theory (Färe and Primont, 1995). Additionally, F and Y in T are supposed to be strongly or freely disposable, i.e. if (F,Y,N) T and $F' \geq F$ (or $Y' \leq Y$) then $(F',Y,N) \in T$ (or $(F,Y',N) \in T$).

Two assumptions have to be made in order to reasonably model a production process in which both desirable and undesirable outputs are jointly produced (Zhou and Ang, 2007). The two such assumptions were introduced by Färe *et al*. (1989) and these are as follows:

1. Outputs are weakly disposable, i.e., if $(F, Y, N) \in T$ and $0 \leq \theta \leq 1$, then $(F, \theta Y, \theta N) \in T$.[24]
2. Desirable and undesirable outputs are null-joint, i.e., if $(F, Y, N) \in T$ and $N=0$, then $Y=0$.

It is necessary to expand on the two assumptions made above. Under assumption (1), the implication is that the reduction of nitrogen surplus is not free and a proportional reduction in production (milk in this case) and nitrogen surplus is feasible. Conversely, assumption (2) implies that nitrogen surpluses must also be produced when milk is produced, which carries the connotation that the only way to eliminate all nitrogen surpluses is to do away with the production process altogether.

The preceding discussion was centred on defining and conceptually locating the suggested technology for modelling the joint production of desirable (Y) and undesirable (N) outputs. Other studies have also attempted to model the joint production of desirable and undesirable outputs. For example, Färe *et al*. (2005) referred to this technology as a polluting technology. The conceptualization process of the model has been sufficiently developed. However, what is still needed is further characterization of the polluting technology within a parametric or a nonparametric framework in empirical studies. The nonparametric approach will be adopted for this study. In the nonparametric construction, the polluting technology can be constructed by the piecewise linear combinations of the observed data. Assume that there are $k=1, 2,\ldots, K$ entities (e.g. farms) and for entity k the observed data are (F_k, Y_k, N_k). Then the piecewise linear polluting technology T can be formulated as follows:

[24] In line with other related studies, the weak disposability of N surpluses as a kind of undesirable output is implicitly assumed although N surpluses are still unregulated in South Africa. Additionally, the growing concern on environmentally benignity of production makes the treatment of nitrogen surpluses as weakly disposable a logical assumption (Zaim and Taskin, 2000).

$$
\begin{aligned}
T = \Big\{ (F,Y,N) : & \sum_{k=1}^{K} z_k F_k \le F \\
& \sum_{k=1}^{K} z_k Y_k \ge Y \\
& \sum_{k=1}^{K} z_k N_k = N \\
& z_k \ge 0, k = 1,2,\dots,K \Big\}
\end{aligned} \qquad \textbf{(9.2)}
$$

T is the environmental DEA technology exhibiting constant returns to scale (CRS) since it is formulated in the DEA framework (Zhou *et al*., 2008).

9.4 Decomposition of the production function

The first step in the composition of the production function is to define two Shephard input distance functions for input (nitrogen fertilizer consumption) and undesirable output (nitrogen surpluses) as follows:

$$D_e(F,Y,N) = \sup\{\lambda : (E/\lambda, Y, N) \in T\} \qquad \textbf{(9.3)}$$

$$D_c(F,Y,N) = \sup\{\theta : (F, Y, N/\theta) \in T\} \qquad \textbf{(9.4)}$$

Equation (9.3) tries to minimize nitrogen fertilizer for the given levels of desirable output (milk), nitrogen surpluses and production technology. Equation (9.4) endeavours to reduce the amount of nitrogen surpluses as much as possible given the nitrogen fertilizer use levels, output and production technology.[25] In addition, the two Shephard input distance functions could also be used to characterize the production technology if appropriate assumptions are imposed (Färe and Primont, 1995).

A graphical illustration of the environmental DEA technology (variable returns to scale) is helpful in understanding the proposed methodology. Here consideration is given to a hypothetical situation of four dairy farms that use equal inputs to produce a desirable output (milk output) and an undesirable output (N). The four farms are labelled A, B, C and D in Figure 32. The environmental output set P3(x) is the region OABCDE except the origin. However, without the adjusting

[25] It should be noted that both De(F,Y,N) and Dc(F,Y,N) are not less than unity as stated by Färe and Primont (1995) in their discussion on the concepts and properties of the Shephard distance functions.

parameter α in P3(x), the region will be FABCDE. It may be concluded that the adjusting parameter α allows P3(x) to possess the two properties (P1′ and P2′) of environmental output sets under VRS.

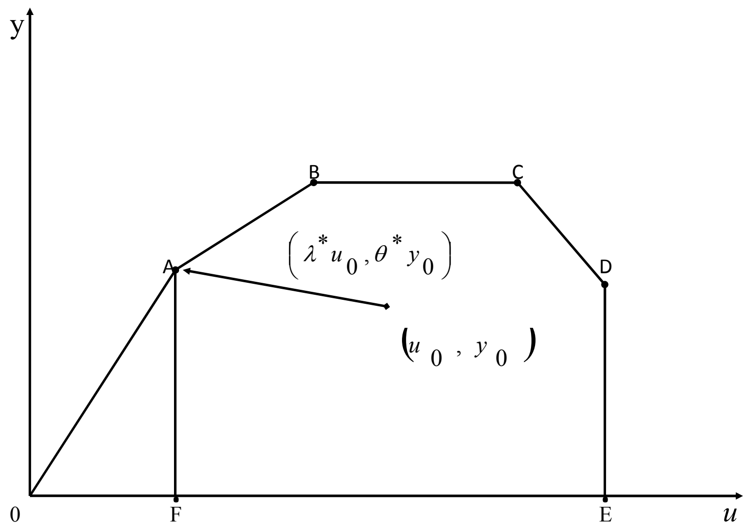


Figure 32: The VRS environmental output set
Source: Zhou *et al.* (2008).

9.5 Data

In this chapter, data describing the production activities of 34 specialized dairy farms in the KwaZulu-Natal Midlands for 2008 were used. The 34 farms used for the analysis of environmental efficiency, using nitrogen, were part of a pasture-utilization study group and the dataset included quantities of fertilizer used thus being suitable for the study. The data was obtained from Allan Penderis of Tammac Consulting who is responsible for coordinating the pasture-utilization study.

The period 2008 was chosen by default because data were available for only this one year even though a panel with a number of years would have been ideal. With panel data it would have been possible to do Malmquist productivity indices for environmental efficiency. However, in reality, the analyses that can be done are also determined by the available data. The dataset of 34 farms was selected because detailed information describing the nitrogen flows at each farm was available and the dataset used in the previous chapters was deficient of such information. The inputs and the output specified were based upon the production process of dairy farms in the area. The production process, including the nitrogen flows, are as depicted in Figures 29 and 30.

Of particular interest, partly because the work reported in this chapter is concerned with environmental efficiency and also because this has not been covered in any of the previous empirical chapters, is how the data for the nitrogen containing inputs and outputs were derived. Firstly the input quantity index consists of nitrogen fertilizer used, roughage and concentrates utilized, and manure. The output quantity index contains milk, meat, livestock and roughage sold. These all contain nutrients, which are depicted in Figure 30. The nitrogen surplus is represented in Figure 30 as the sum of 'nutrient exchange with the soil' and 'ammonia from land'. The nitrogen surplus, the difference between nitrogen input and nitrogen contained in desirable outputs, is measured in kilograms. The characteristics of the data set are summarized in Table 59. The variables used for the environmental efficiency analysis were roughage (pasture) area allocated to the dairy herd measured in hectares; mature herd size (number of cows); all concentrates used (kilograms of dry matter per hectare - kg/DM/ha); nitrogen fertilizer applied (kg/ha); output in milk produced (l/ha/year) and nitrogen balance/ surplus (kg/ha).

Table 54: Summary of the variables used for environmental efficiency

Variable	Unit	Statistic			
		Mean	STDEV	Max	Min
Roughage area allocated to dairy herd	ha	223.6	131.5	650.0	75.8
Mature herd size	number	336.6	151.6	776	96
Concentrates (all) used	kg/DM/ha	8.8	4.0	21.0	1.1
Nitrogen (N) used	kg/ha	228.2	90.8	482.5	69.0
Milk produced	l/ha/year	9788.2	3159.5	17174.0	3597.4
N Balance	kg/ha	575.4	111.6	887.4	373.3

Table 59 shows the summary statistics of the 34 farms studied. It can be observed that the farms came in different sizes with a wide range as indicated by the roughage area allocated to the dairy herd. The average area was 223.6 ha, with the smallest farm being only 75.8 ha and the biggest farm almost eight times larger at 650 ha. Although there was a big difference between the smallest and largest farm, the standard deviation of 131.5ha indicates that most of the farms were distributed around the means of 223.6 ha. Looking at the productive herd size (mature herd size) the picture is similar with the largest farm, in terms of herd size, having 776 mature cows and the smallest having only 96. The average mature herd size was 337 cows with a standard deviation of 151.6. All 34 dairy farms used concentrate feed to supplement grazing, which supplies roughage and energy to the cows. Notwithstanding that dairy production in South Africa is predominately pasture-based, the use of concentrate feed (normally referred to as concentrates) is quite common. Concentrates are mainly used to provide protein, since milk production can deplete a cow's protein reserves, vitamins and minerals. The amount of concentrates used varied widely across the farms with an average of

8.8 kilograms of dry matter per day (kg/DM/day), a maximum of 21 and a minimum of 1.1 kg/dm/day.

Of particular interest are nitrogen utilization and milk output, because these two indicators have a substantial bearing on the nitrogen balance on the farms. The milk yield/production exhibited a wide range with the least producing farm having 3 597 litres per hectare per year (l/ha/year) and the highest having almost five times the amount at 17 174 l/ha/year. The amount of nitrogen fertilizer used was no different from the variables already discussed in that there were marked inter-farm differences with a standard deviation of 90.8 kg of nitrogen per hectare. The most nitrogen-frugal farm used 69 kg/ha, while the most lavish used 482 kg/ha. All the differences discussed above ultimately manifested themselves in the differences in the nitrogen balances between farms. The mean nitrogen balance of 578.5 was higher than the mean fertilizer nitrogen applied of 482, which indicates that there is scope to reduce nitrogen application without stifling production.

9.6 Results

9.6.1. Standard cost and returns analysis for the dairy farms

Before the DEA application, a standard costs and returns analysis was performed for all 34 farms to see if the average economic results of the nitrogen fertilizer technology yield useful information. Table 60 presents the analysis. Gross value of production and total costs of nitrogen fertilizer use for the dairy farms are provided. The analysis of costs of nitrogen fertilization as a proportion of the gross value of production (a product of milk output and milk price per litre) gives an indication of the magnitude of the cost of applying nitrogen to the soil The costs:returns ratio undergirds the importance of using only the required quantities of the nitrogen input and guarding against prophylactic application. Caution should be taken, however, that in the quest to minimize the amounts of nitrogen applied, thereby minimizing nitrogen surplus, one should not skimp on applying the required levels to achieve the desired output levels of pasture yields.

Table 60: Milk production costs (N fertilizer only) and returns per hectare

Item	Unit	Value	Standard deviation
Observations		34	-
N fertilizer usage	kg/ha	228.18	90.83
Cost of N fertilizer use	R/ha	3 088.14	1408.34
Costs and returns			
Gross value of production	R/ha	3 161 698	220 0128
Costs of N fertilization	R/ha	690 399.3	48 3406.1
Costs : Returns Ratio		0.22	

9.6.2 Environmental efficiency

Before looking at environmental efficiency[26], which is the raison d'être for this chapter, a brief analysis and discussion of technical efficiency[27] is warranted to put things into perspective. It is important to establish if environmental efficiency and technical efficiency are mutually exclusive for the farmers in the sample, that is, to see if environmental efficiency can be achieved without sacrificing technical efficiency. Table 61 shows both the technical and environmental efficiencies of the dairy farms studied. Technical efficiency is shown in the second column. Eight farms were found to be fully technically efficient, i.e. having unitary (1) technical efficiency and the average technical efficiency of the sample was moderate at 0.779 (77.9%) implying that there is scope to improve efficiency by more than 22 percent (22.1%). Farms 1, 8, 22, 24, 26, 27, 30, and 31 were the efficient farms, and thus defined the production frontier. It is interesting to observe the wide range in the efficiencies of the farms, with the poorest performing farm (farm 18) having an efficiency score of 0.459 when compared to the efficient farms (1.000). Another interesting point to note is that a lot of the farms, however, were distributed around the mean as indicated by the median value of 0.735 (only 0.044 less than the mean).

Next is a look at the environmentally-adjusted efficiency scores, where nitrogen surplus was used as the polluting output (undesirable output) or environmentally-detrimental by-product of the dairy production system (nitrogen emission to the environment). These environmental efficiency scores are shown in the third column of Table 61. Unlike with technical efficiency, where eight farms were efficient, only four farms were found to be environmentally efficient. Interestingly, all four of the farms that were environmentally efficient, namely farms 1, 8, 22 and 24, were also technically efficient.

The average environmental efficiency was 0.738 (73.8%) and was lower than the technical efficiency average, meaning that the farms were less environmentally efficient than they were technically efficient. This observation is hardly surprising as most farmers are more preoccupied with technical efficiency than being environmentally benign in their production. The apparent lack of focus on environmental efficiency could be a result of the absence of any incentives to be ecologically friendly, as there is no current legislation to that effect in South Africa. The other possible reason could be the difficulty of recommending the correct amount of nitrogen fertilizer to

[26] Environmental efficiency refers to the efficiency value obtained using two outputs, namely, milk output as the desirable output, and nitrogen surplus as the undesirable output. The inverse of the nitrogen surplus was used in this study because the DEA programme (DEAP) reads high numbers as being more efficient than lower numbers. However, in the case nitrogen surplus, the lower the value the more efficient the farm is.

[27] Technical efficiency here refers to the simple efficiency value obtained using one output, milk output as the dependent (output) variable.

be applied due to the lack of an accurate soil nitrogen predicting method. Nitrogen is currently applied following general broad guidelines determined by the crop being grown and soil type. This does not take into account the inherent nitrogen content of the soil and residual amount of nitrogen from previous applications, animal excretion, atmospheric and biological fixation of nitrogen.

Table 61: Technical and environmental efficiencies of the 34 farms

Farm	Technical Efficiency	Environmental Efficiency
1	1	1
8	1	1
22	1	1
24	1	1
26	1	0.99
27	1	0.962
30	1	0.875
31	1	0.855
7	0.962	0.834
28	0.95	0.828
34	0.875	0.826
5	0.858	0.803
33	0.826	0.781
12	0.781	0.769
9	0.764	0.759
19	0.759	0.723
20	0.751	0.719
21	0.719	0.703
10	0.716	0.701
15	0.716	0.692
3	0.692	0.666
25	0.687	0.643
13	0.672	0.641
11	0.67	0.636
17	0.667	0.622
14	0.666	0.619
29	0.666	0.616
16	0.643	0.614
6	0.638	0.608
32	0.622	0.601
4	0.619	0.589
2	0.601	0.53
23	0.503	0.459
18	0.459	0.43
mean	**0.779**	**0.738**

The results discussed can also be presented graphically as shown in Figure 33. The graphical representation of the results facilitates a better visualization of the distribution of efficiencies across farms. From the results, it can be observed that farms tend to be more efficient technically than they are environmentally.

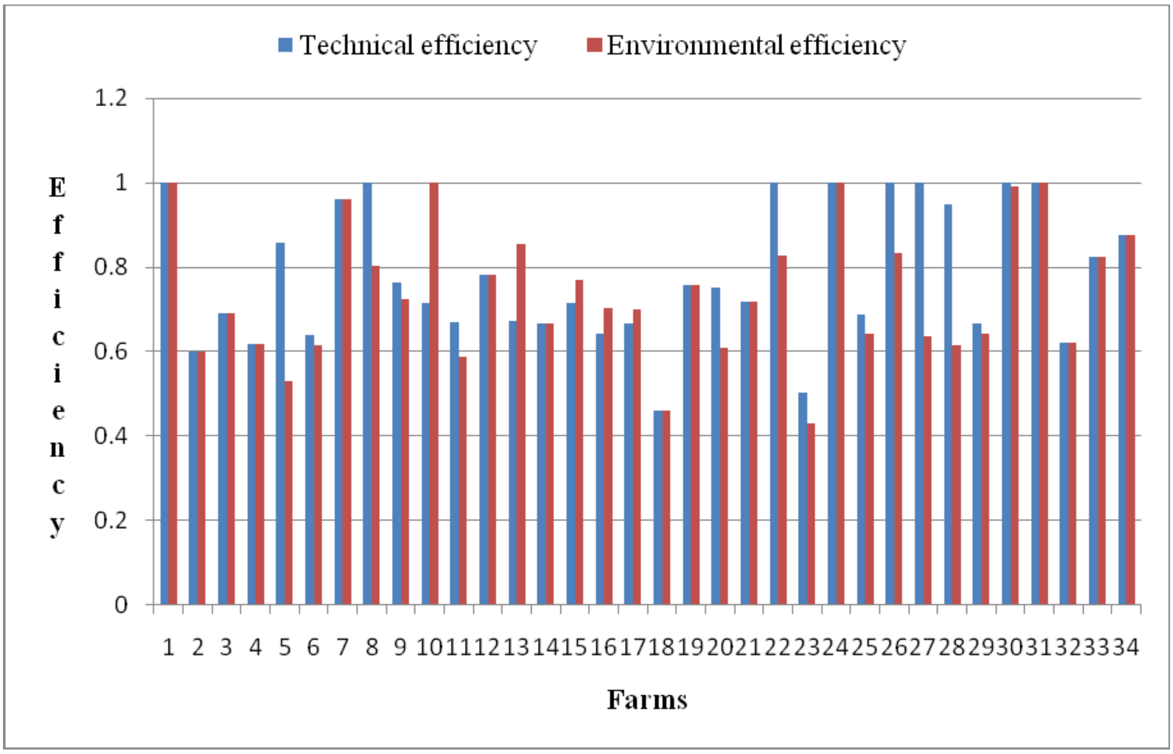


Figure 33: Technical and environmental efficiencies of the 34 farms

The positive correlation between technical and environmental efficiencies indicates that farms which tend to be less efficient technically also tend to be less efficient environmentally as shown in Figure 34. Table 62 further illustrates the close correlation between technical efficiency and environmental efficiency using both the Spearman correlation and Ktau correlation, which is more suitable for analysing correlation in small samples (StataCorp, 2009). The Spearmen correlation of 0.994 and the Ktau correlations of 0.946 (Kendell's tau-a) and 0.976 (Kendell's tau-b) are very close to one, implying that there is no necessary trade-off between environmental and technical efficiencies, thus farms can be both technically and environmentally efficient.

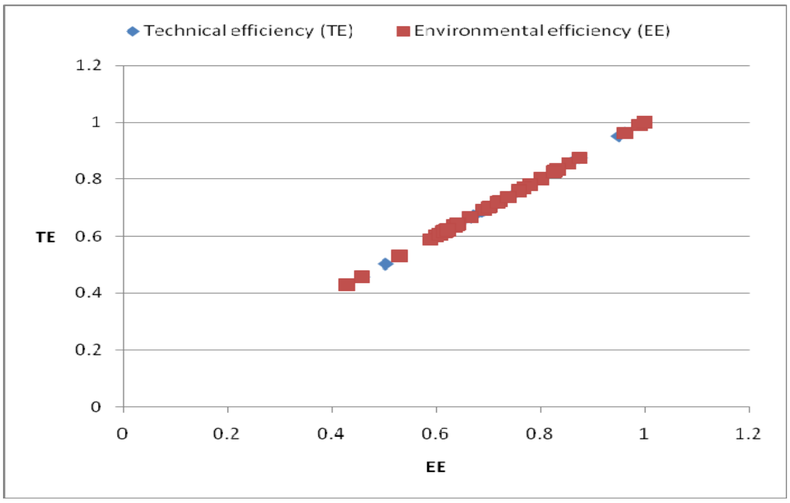


Figure 34: Correlation between technical efficiency and environmental efficiency

This is an important finding in terms of farms being environmentally benign without compromising their technical efficiency and this is in agreement with the basic result of a negative elasticity on nitrogen in the SF regressions reported in Chapter 8. There was also a large spread of efficiencies across farms for both technical and environmental efficiencies. The null hypothesis of technical efficiency and environmental efficiency being dependent is rejected because the results show that they are independent of each other although highly correlated.

Table 62: Spearman and Ktau correlation between technical and environmental efficiency

Number of observations	34
Spearman's rho	0.9944
Test of Ho: technical efficiency and environmental efficiency are independent	
Prob > t	0
ktau	
Number of observations	34
Kendall's tau-a	0.9462
Kendall's tau-b	0.9759
Kendall's score	563
SE of score	69.876 (corrected for ties)
Test of Ho: technical efficiency and environmental efficiency are independent	
Prob > z	0.0000 (continuity corrected)

The next step is to look at the environmental efficiency results as presented in Table 63, which shows the results of environmental efficiency using only the undesirable output, N surplus, instead of the two-output approach that was adopted in the previous section. A cautionary note here is that it is difficult to conceptualize putting in milk as an input, which is clearly an output, and still be able to defend such. However, it was necessary to include milk as an input because it would be difficult for farmers to embrace any suggestions to improve environmental efficiency if this came at the price of reducing milk, thus reducing income. The results show that the average environmental efficiency of the 34 was 58.4 percent (0.584) which is quite low and not widely dispersed as shown by the standard deviation of 0.285. There are five farms that define the environmental efficiency frontier, namely: Farm 1, 4, 10, 15, and 27. These farms are therefore considered as benchmarks for the 34 farms analyzed.

The worse performing farm was farm 30, which recorded an environmental efficiency of 0.109. A closer look at farm 30 reveals a number of tell-tale observations: 1) it was the largest farm with a total roughage area allocated to the dairy of 650 ha and a mature herd size of 776 cows although 2) the quantity of nitrogen fertilizer used per hectare was modest by sample standards, 191.6 kg of nitrogen compared with the mean of 228.18 kg nitrogen. However, when taking into consideration the total quantity of nitrogen fertilizer applied farm 30 was by far the largest consumer of nitrogen. This is to be expected as farm size is postulated to have a positive effect on the quantity of nitrogen applied. 3) farm 30 imported almost 40 percent (38.4%) of the total feed for dairy production which was high considering that the dairy farms in the sample are predominantly pasture-based. From the total sample, there appears to be strong relationship between the percentage of feed brought into the farm from outside sources (imported) and the quantity of nitrogen surplus.

Table 63: Environmental efficiency of the 34 dairy farms studied

Farm	Technical efficiency	Environmental efficiency
1	1	1
2	0.601	0.461
3	0.692	0.282
4	0.619	1
5	0.53	0.392
6	0.614	0.293
7	0.962	0.448
8	0.803	0.356
9	0.723	0.266
10	1	1
11	0.589	0.818
12	0.781	0.381
13	0.855	0.791
14	0.666	0.231
15	0.769	1
16	0.703	0.659
17	0.701	0.535
18	0.459	0.35
19	0.759	0.282
20	0.608	0.537
21	0.719	0.994
22	0.828	0.676
23	0.43	0.558
24	1	0.903
25	0.643	0.35
26	0.834	0.761
27	0.636	1
28	0.616	0.83
29	0.641	0.856
30	0.99	0.109
31	1	0.393
32	0.622	0.279
33	0.826	0.797
34	0.875	0.278
mean	**0.738**	**0.584**

Figure 35 provides a graphical rendition of the distribution of the 34 farms according to their environmental efficiencies.

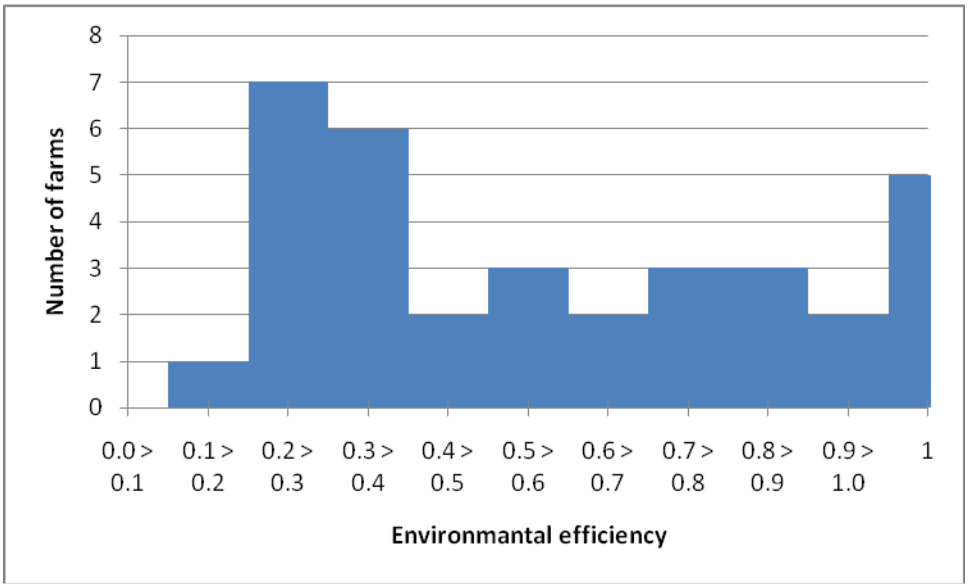


Figure 35: Distribution of farms according to environmental efficiency

The categories were divided into intervals of 0.1 exclusively (efficiency scores falling within the defined range, excluding the starting and end points). There were no farms falling with the first category of 0.0 > 0.1, and only one farm in the 0.1 > 0.2. The bulk of the farms fell within the 0.2 > 0.3 and 0.3 > 0.4 categories, with seven farms in the first and six in the second. Thirteen farms fell between category 0.4 > 0.5 to 0.9 > 1.0 and there were five farms that were environmentally efficient. The DEA defines efficiency according to the data provided, thus any efficiency is relative to the best farm within the sample. As a result, care should be taken in understanding the environmentally efficient farms. The efficient farms are only efficient when compared among their peers. Having mentioned peers, it becomes necessary to discuss the subject and also to look at what the results show in relation to peers.

9.6.3 Peers and peer weights

Table 64 shows the peers for each farm and the weights that these peers account for. For each inefficient farm there are peers which serve as comparators against which the farm is measured. Efficient farms do not have any peers other than themselves, as they are on the environmental efficient frontier thus defining the efficiency. It stands to reason that the weight will be unity in the case of efficient farms.

Table 55: Peers and peer weights for each of the 34 dairy farms

Farm	Peers (peer weights)		
1	1 (1)[28]		
2	4 (0.251)	15 (0.366)	
3	4 (0.285)	27 (0.201)	
4	4 (1)		
5	10 (0.093)	1 (0.233)	
6	10 (0.137)	1 (0.219)	
7	15 (0.45)	4 (0.116)	1 (0.021)
8	1 (0.152)	15 (0.371)	
9	4 (0.08)	1 (0.171)	15 (0.08)
10	10 (1)		
11	27 (0.336)	15 (0.45)	
12	10 (0.13)	1 (0.427)	
13	1 (0.439)		
14	1 (0.231)		
15	15 (1)		
16	1 (0.512)		
17	1 (0.475)		
18	10 (0.018)	1 (0.103)	
19	10 (0.164)	1 (0.185)	
20	1 (0.418)		
21	15 (0.167)	4 (0.702)	27 (0.152)
22	1 (0.418)	15 (0.002)	
23	4 (0.104)	1 (0.303)	
24	1 (0.334)	10 (0.624)	
25	1 (0.046)	15 (0.334)	
26	15 (0.273)	4 (0.227)	1 (0.114)
27	27 (1)		
28	10 (0.402)	1 (0.241)	
29	15 (0.614)	4 (0.307)	27 (0.114)
30	10 (0.027)	1 (0.088)	
31	1 (0.466)		
32	1 (0.248)		
33	1 (0.116)	15 (0.52)	
34	10 (0.014)	1 (0.412)	

Only the efficient farms serve as peers for the inefficient farms and in this instance farms 1, 4, 10, 15, and 27 are the peers. Farm 1, for example, was a peer for 13 farms making it the most used farm as a comparator. Turning to peer weights, the higher the weight the more important that particular farm is as a peer for the inefficient farm in question. This means that the inefficient farm is better off comparing itself to the peer with the highest weight in order to improve its environmental efficiency by emulating its peers. The identification of peers is important in that the peers' production technology, in this case pollution minimizing technology, can be studied and implemented by the inefficient farms.

[28] Figures in parendissertation denote peer weights. These weights are the most favourable ones from the point of view of the target unit. To obtain the efficiencies of the entire set of units it is necessary to solve a linear program focusing on each unit in turn.

9.6.4 Radial measures of environmental efficiency and slacks

Before discussing the slack results it would suffice to briefly recap on the concept of slacks within the DEA approach and how these are calculated. Figure 36 illustrates the concepts of radial measures of environmental efficiency (EE) and slacks. An isoquant producing some fixed level of output Y using two inputs, X_1 and X_2 is shown. The efficiency frontier depicted is defined by farms A and B, which use fewer inputs than C. If farm C was to retain its input ratio but reduce the levels used until it is efficient, it would be at point C*. Thus, farm C's efficiency is EE = 0C*/0C. This reduction in inputs is called the radial efficiency measure.

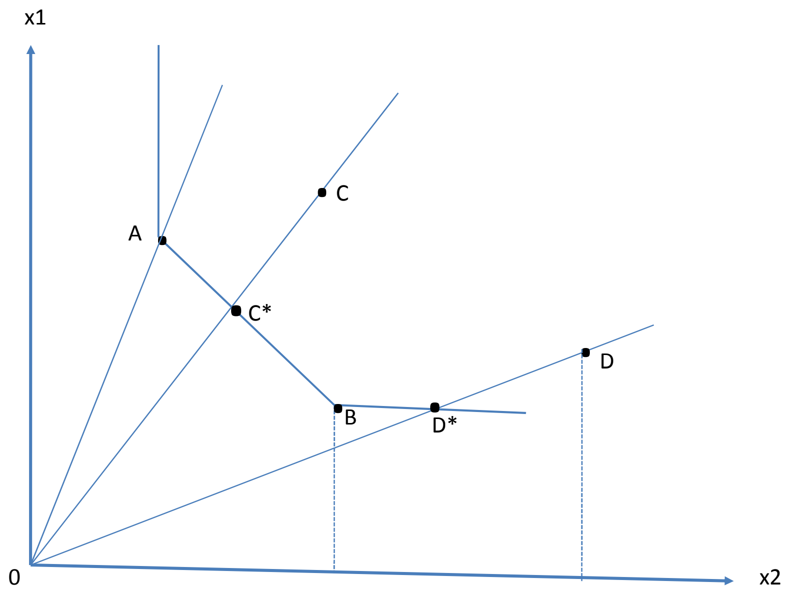


Figure 36: Radial measures of environmental efficiency and slacks

Farm D can similarly radially reduce its inputs from D to D*, but, beyond point B using more X_2 does not increase output. Thus X_2 is a slack variable for this farm and it can also be reduced by BD* of input X_2 without loss of output. In the results discussed in this chapter fertilizer is a polluting input which can be viewed as a slack variable for the dairy farms as the application of nitrogen fertilizer can be reduced, to a certain extent, without reducing milk output but reducing nitrogen surplus (detrimental or undesirable output).

In the current study both milk production and nitrogen surplus can be viewed as outputs with milk output a desirable output and nitrogen surplus an undesirable output (sometimes referred to as the 'bad' or pollutant). The objective here would be to reduce the amount of nitrogen surplus to zero, if possible, thus attaining the materials balance equilibrium (Coelli *et al.*, 2007; Tyteca, 1995), thus the aim is minimizing nitrogen inputs without adversely affecting the production of milk and other desirables (meat and pasture). The results of the undesirable output slacks are presented in Table 65, which indicates the scope for reducing the output of the nitrogen surplus, which is a pollutant, without reducing the output of milk. It is interesting to note that even the environmentally efficient farms can still reduce their emissions of nitrogen to the environment. However, the efficient farms can easily achieve the reduction of nitrogen inputs since they only have to do minor adjustments to their production technology.

The farms with lower environmental efficiencies have to reduce their emission of nitrogen by bigger amounts as this is the reason *par excellence* why they are environmentally inefficient. Table 66 shows output slacks for the 34 farms. Output in this case refers to the undesirable output (N surplus) and not the desirable output (milk). For example farms 3, 18 and 30 need to reduce their N surpluses by 333.3 kg to attain environmental efficiency at the same time maintaining the same level of the desirable output (milk).

Table 56: Output slacks for the 34 dairy farms

Farm	Output slacks
1	37.04
2	142.86
3	333.33
4	166.67
5	125.00
6	125.00
7	125.00
8	111.11
9	166.67
10	58.82
11	111.11
12	71.43
13	83.33
14	166.67
15	71.43
16	71.43
17	76.92
18	333.33
19	125.00
20	90.91
21	125.00
22	90.91
23	111.11
24	50.00
25	166.67
26	125.00
27	125.00
28	76.92
29	90.91
30	333.33
31	76.92
32	142.86
33	90.91
34	90.91

Lastly, a look at the inputs slacks is warranted as this is where the farmer has room to manoeuvre in trying to achieve environmental efficiency. The input slacks of the sample of farmers are reported in Table 66. Inputs slacks indicate the amount by which each input is over-used. Put differently, the slacks indicate the amounts by which each input can be reduced to minimize nitrogen surplus while keeping milk output unchanged.

Table 66: Input slacks for the 34 dairy farms

Farm	Input				
	Milk output (l/ha)	**Roughage area (ha)**	**Number of mature cows**	**N fertilizer (kg/ha/pa)**	**Imported feed (kgDM/ha)**
1	0	0	0	0	0
2	0.174	0	7.339	54.912	0
3	0.072	0	0	76.671	13.041
4	0	0	0	0	0
5	0	51.362	65.344	101.412	0
6	0	12.099	34.914	78.997	0
7	0	0	0.06	26.685	0
8	0.65	0	12.47	50.123	0
9	0	0	26.248	56.431	0
10	0	0	0	0	0
11	1.886	0	0	73.739	126.854
12	0.198	85.186	0	60.422	0
13	0	541.502	49.332	86.715	140.027
14	0	125.025	47.553	76.825	3.402
15	0	0	0	0	0
16	0	276.984	44.161	72.016	7.736
17	0	189.779	28.669	70.931	9.154
18	0	159.837	217.001	159.036	0
19	0	128.642	37.896	67.339	0
20	0	170.684	48.912	77.003	14.637
21	4.166	0	0	110.295	0
22	1.626	0	80.928	98.063	0
23	0	0	51.428	103.378	25.193
24	5.268	180.746	0	75.66	0
25	0.076	0	69.175	80.934	0
26	0	0	40.121	50.137	0
27	0	0	0	0	0
28	0	474.014	44.584	139.24	0
29	2.645	0	0	72.339	0
30	0	50.68	60.098	71.73	0
31	2.087	35.459	0	67.941	81.114
32	0	18.302	43.939	59.562	32.705
33	8.35	0	101.714	356.871	0
34	0.09	5.146	0	51.07	0
mean	**0.803**	**73.69**	**32.703**	**74.308**	**13.349**

Milk output was included as an ‘input’ in this analysis to ascertain if a reduction in milk output would result in a corresponding reduction nitrogen surplus. The main intention of including milk output as an input was to see if there is any substance to the prevalent sentiment in environmental protection circles in South Africa that increasing output of agricultural production will invariably lead to environmental degradation. Clearly, it can be seen from the results that there is minimal "over-usage" (over production) of milk thus reducing milk output on its own will not lead to improved environmental efficiency. The roughage area allocated to the dairy herd (farm size), the number of mature cows (herd size), and the quantity of nitrogen fertilizer applied present the best scope for reducing nitrogen surplus thus improving environmental efficiency of the dairy farms. The area of imported feed also provides some room for reducing nitrogen surplus by relying more on home grown feed. This should not be difficult because dairy farmers in the KwaZulu-Natal Midlands have developed the necessary competence over the years to produce most of the feed themselves, except for concentrates for protein supplementation in the diet.

In summary, milk production would have to be reduced by 0.8 litres per hectare; land (roughage area allocated to the dairy herd) by 73.69 ha; number of mature cows by 33 cows, nitrogen fertilizer application by 74.3 kilograms per hectare; and imported feed (mainly concentrates) by 13.4 kilograms of dry matter per hectare. The adjustments that would be required if environmentally inefficient farms were to adopt best practice technology and move towards their environmental production frontiers indicate that the production of pollutants (nitrogen surplus) could be reduced at negligible cost to milk production. The positive correlation between technical and environmental efficiencies indicates that improving environmental efficiency could be associated with improvements in technical efficiency. Thus, policies aimed at improving efficiency, such as educating farmers in best practice technology, could have substantial rewards. Furthermore this positive correlation between the two forms of efficiency signifies that reduction in milk production should not be necessary.

Chapter 10: Conclusions and policy recommendations

10.1 Introduction

The South African agricultural sector has undergone major structural and policy shifts over the last 15 years. Before the advent of democracy the dairy industry, in keeping with the rest of the agricultural economy, was highly regulated under the dairy board and production was controlled through quota allocations to farmers. In the 1990s the dairy industry was deregulated as the new South African government liberalised the economy. The deregulation of the dairy industry was accompanied by a shift of production from inland areas, such as Gauteng, Free State and Mpumalanga, to coastal areas, such as KwaZulu-Natal, Western Cape and the Eastern Cape. Another conspicuous trend since the deregulation is the phenomenon of a number of dairy farms exiting the industry annually and dairy farms becoming bigger in size.

Looking at the trends in the dairy industry also shows that dairy farms now produce more milk per cow per year. The prices of milk per litre that the farmers receive have remained low and sometimes the real change in the farm gate price of milk declined year-on-year. In addition, the costs of inputs used for dairy production have been on an upward trajectory that has eroded any increases that might have occurred in the price of milk. The disparities between the cost of production and farm income have put profitability pressures on the farms, forcing a number of them out of business and demanding increased efficiency on those remaining in order for them to be viable in the medium to long term. The scenarios outlined here vindicate the relevance of the study and its timeliness.

Since the deregulation of the industry, there has been substantial restructuring of both the dairy production and processing sectors in an effort to improve global competitiveness. A significant confidence indicator in the restructuring of the processing sector, in particular, was been the substantial investment of multinationals such as Parmalat and Clover/Danone in large South African dairy companies, and the continuing presence of Nestlé.

The main objective of the dissertation was to define the production possibility frontier of the KwaZulu-Natal Midlands dairy industry. This was addressed by breaking it into two further objectives, namely the estimation and calculation of technical efficiency of the dairy farms and the estimation and calculation of the environmental efficiency of the farms in the Midlands of KwaZulu-Natal. Both technical efficiency and environmental efficiency were estimated econometrically following the parametric stochastic frontier (SFA) approach, and then calculated following the nonparametric mathematical data envelopment analysis (DEA) approach.

10.2 Review of literature

In Chapter 2 an overview of production economics and an introduction to the analytical concepts or tools that were used for analyzing the data in the results chapters was provided. These production functions and other production economics concepts were further expanded upon in subsequent chapters where they were used for better conceptualization and comprehension. From the literature surveyed for the purposes of this dissertation, it could clearly be established that variations in efficiency and productivity are common in the agricultural sector in general, and the dairy subsector in particular, the world over. This conclusion buttresses the need for production economists and econometricians to develop the analytical tools and the empirical techniques needed to study the subject of production efficiency. The ability to quantify variation in efficiency and productivity and to identify its sources makes it possible to adopt private firm practices and public policies designed to improve it. Motivations for the study of efficiency and productivity and the theoretical underpinnings were provided.

10.3 Modelling the efficiency of dairy farms

In most empirical studies of efficiency in dairy farming, output and input variables included have been determined largely by data availability. Often the only output is milk and less important outputs like farm grown feed, culled cows and male calves that are sold, have been ignored. Perhaps the most interesting issue is the inclusion of the dairy herd as an input, which is done in some studies, but not others, with the decision again based mostly on data availability. In this case, there is detailed farm accounting data for nine years, on 37 dairy farms. The purchased inputs are aggregated to land, labour, feed, veterinary expenses, milking facility costs and other machinery. The final outputs are milk, surplus feed that is sold and beef animals, which are the value of culled cows and male calves, minus the cost of any dairy cows purchased.

These variables are used in the net outputs approach, which avoids using farm produced inputs. Thus, cows do not appear as an input, although it is not possible to produce milk without them, because they are both produced and consumed on the farm and so can be subtracted from both sides of the accounts. Cows would only appear in the equations if a gross output approach is used and then the gross investment in the herd (new animals added) should appear as an output and be balanced on the input side by depreciation on the herd, not the entire stock of animals.

The gross approach is modelled first as a system of three simultaneous equations, for milk, cows and feed. This is followed by single equation models that allow production frontiers to be fitted, which give efficiency estimates for each farm in every year. The statistical tests all favour the theoretically incorrect models that include cows as an input, although this is both double counting of inputs and mixing stocks and flows. The most sensible compromise between correct accounting on the one hand and better test statistics on the other is to opt for Battese and Coelli's (1995) inefficiency model, in which the herd size can be included in the terms that explain the inefficiencies rather than in the frontier itself.

This approach results in TL models where so much is explained that there is either no room for all the TL terms or for inefficiencies. What was clearly a frontier verges on becoming a mean response function because there is little residual left to define inefficiencies. This is resolved by dropping the insignificant squared and cross product terms in the TL and including inefficiencies. This gives a model in which all the inputs are significantly different from zero in the frontier estimates, while capital investment and herd size reduce the inefficiencies and the proportion of cows that are dry increases them.

The results of the work reported in this dissertation have shown that modelling of dairy farms is not straightforward but it is complex due to the multiple-inputs, multiple-output nature of production. Furthermore, some of the outputs produced are used in the production of other outputs thus rendering such outputs as intermediate outputs. All the inputs used and outputs generated need to be accounted for in order to properly represent and describe the dairy production system. The proper modelling of the dairy industry is important because without such it would be difficult to estimate any meaningful production function of the system.

The approach that was adopted in modelling the dairy industry in South Africa was to work in terms of net outputs and inputs. The key concept was that when an input purchased off the farm crosses the farm gate it has to be recorded on the input or negative side of the balance sheet. Outputs are on the positive side of the balance sheet, and are only recorded when the product leaves the farm to enter the rest of the economy. The reasoning was that if an input such as animal feed is produced on the farm and consumed by farm animals it is the milk or meat resulting from the animal that is recorded as an output. The farm produced input is usually not measured at all. If it were measured, an alternative approach could be taken and the accounts worked on the basis of gross outputs and inputs. This is the approach towards which the EU farm accounting schemes are moving. If the gross basis is used, then farm produced feed would be recorded both as an input and as an output. It is exactly because it appears on both sides of the balance sheet that it can be subtracted from both sides without causing any error. This makes the accounts simpler by removing several items that are hard to measure because they are produced and consumed on the farm.

The modelling results showed the importance and the requirement for good quality data in order to be able to select the relevant variables. The dataset used for the analysis was less than ideal, which is often the case in analyses of this nature, but deflation and aggregation techniques mitigated some of these weaknesses. The results highlighted the ever present need for good data. The conclusion that can be drawn in terms of data is that there is a paucity of good and reliable time series data for production and price variables in the dairy industry in South Africa.

10.4 Alternative empirical approaches to production functions estimation

Next, conclusions are drawn from the results of the alternative empirical approaches to production function estimation of the dairy farms in the KwaZulu-Natal Midlands presented in Chapter 5. The analyses in Chapter 5 used stochastic frontier and inefficiency models to test the efficiency of dairy production. The estimation of the stochastic production frontier and the associated technical efficiency model were done to determine the importance of inputs in dairy production and the farm-specific characteristics that explain differences in efficiency across dairy farms. The data covers a panel of 37 dairy farms for the period 1999 to 2007 rendering the dataset adequate to allow complex analyses and reveal that the CD stochastic production frontiers, with variables to explain the inefficiencies are an appropriate representation of the sample.

The stochastic frontier results indicated that output could be explained by land, cows (herd size), labour (labour wage as a quality of labour variable), milking machinery and other machinery (cost of running these machinery categories) and that efficiency can be affected by labour quality, percentage of dry cows in the herd, herd size, capital investment and the passage of time. Efficiency was also dependent on farm size and/or herd size, so returns to scale were further investigated using data envelopment analysis to elucidate which quartile of farms were more scale efficient than the rest.

Although the dataset used was good enough to produce reasonable results without pooling, it must be conceded that most researchers in applied economics would consider the possibility of improving the estimates by pooling the samples. Pooling tests performed in this chapter showed that in this situation, given the small sample, pooling may not be helpful.

It is clear that in South Africa dairy farms are becoming fewer and bigger but what is not clear is what is driving this trend. This trend has led to consolidation and increased farm sizes, particularly in the coastal areas of South Africa (i.e. KwaZulu-Natal, Western Cape and the Eastern Cape). Although the results indicated that there are increasing returns to scale (IRTS) in KwaZulu-Natal Midlands dairy farming, the consolidation of farms cannot entirely be explained by IRTS. Cost of production (COP) accounting estimates clearly show that average costs decline as herd sizes increase, and they provide some useful information for assessing the sources of the cost advantage, but they also have limitations which are largely consequences of the data used. Because the data and ultimately the estimates of COP do not distinguish between input quantity and input price, it is not possible to determine whether a cost advantage derives from more efficient input use or from lower prices paid for the input in question. Mkhabela and Mndeme (2010) in their investigation of the cost of producing milk in the KwaZulu-Natal found that there was reduction in the unit cost of producing milk as farm size increased. Furthermore, COP estimates reflect the average performance of farms in each size category while it is known that farms vary in efficiency, some are best-practice efficient operations (frontier makers), while others may be poor performers. Consequently, costs can fall as herd sizes increase, either because larger enterprises tend to be more efficient or because technology creates scale economies that allow large enterprises to realize lower costs than equally efficient smaller enterprises.

10.6 The DEA approach to technical efficiency

The stochastic analyses of efficiency were followed by reporting results from the DEA analyses. As has already been indicated, the results of an efficiency study can be sensitive to the method selected to estimate the efficiency scores. The two most popular techniques used to measure farm efficiency are the DEA and SFA. The former uses mathematical linear programming methods, whereas the latter uses econometric methods. It should be borne in mind that the choice of which method to use is in no way obvious, but has to be decided upon in every case.

The quality of the data, the appropriateness of various functional forms, and the possibility of making behavioural assumptions influences the relative appropriateness of DEA and SFA. For example, the DEA approach does not require any specific functional form to be selected, neither are any behavioural assumptions needed as long as allocative efficiency is not considered. However, DEA is a deterministic approach, meaning that it does not account for noise in the data. All deviations from the frontier will thus be accounted for as inefficiencies. Therefore the DEA efficiency scores are likely to be sensitive to measurement and random errors. Conversely, the SFA accounts for random errors and has the advantage of making inference possible. However, SFA is sensitive to the choice of functional form. Obviously, choosing between parametric and nonparametric methods is a delicate matter and some studies comparing the results of two approaches have been done.

There was a two-fold aim for this chapter. First, it was to compare the relative appropriateness of DEA and SFA in estimating efficiency scores in dairy production. Second, it was to use the results from this analysis to establish measures of efficiency of dairy farms in the KwaZulu-Natal Midlands, and how the efficiency measures are influenced by farm size. Considering the changing structure and market situation of these farms, studies of the economic input efficiency are of high importance to understand the challenges facing the dairy farmers. As the trend in the South African dairy farms seems to be towards bigger herds it will also be interesting to investigate the relationship between efficiency and farm size.

The DEA analysis readily identified specific input inefficiencies for the dairy farms in the sample. Firstly, too much feed and veterinary services were used by the inefficient farms. Secondly, the identification of those inputs that are over-utilised helps in identifying different production trajectories for the inefficient dairy farms to become efficient. Secondly, the DEA approach has the advantage of being able to identify the most appropriate benchmarks for the inefficient farms to imitate and gives another view on returns to scale.

10.7 Measuring environmental efficiency: the stochastic frontier analysis approach

The major drawback of the research presented here, in terms of environmental efficiency, is inability to accurately estimate the quantities of nitrogen inputs and outputs to and from the production system and so calculate the balance of nitrogen which may be available to be leached. However, the nitrogen inputs and outputs were calculated as accurately as possible based on the available data. The conclusions are drawn from results of environmental efficiency calculated as a single-factor measure of input-oriented technical efficiency. Furthermore, it was shown in this study how environmental efficiency can be estimated within a stochastic TL production frontier. It was found that the dairy farms in the Midlands of KwaZulu-Natal achieved relatively low technical efficiency, 0.66 on average. By contrast, the dairy farms achieved generally higher levels of environmental efficiency (0.77 on average, with the best achieving 0.85). Lastly, the results showed that technical efficiency and environmental efficiency were independent for the farms in the sample.

10.8 Measuring environmental efficiency: the DEA approach

In the last empirical chapter (Chapter 9) the environmental efficiency results of 34 dairy farms participating in a pasture-utilization study following the DEA approach were reported. Given that the elasticities for the nitrogen surplus variable varied across farms and the fact that the DEA is more accurate in the sense that the coefficients (elasticities) are calculated rather than estimated, it was deemed necessary to also analyse environmental efficiency using the DEA approach.

In summary, milk production would have to be reduced by 80 litres per hectare; land (roughage area allocated to the dairy herd) by 73.69 ha; number of mature cows by 33 cows, nitrogen fertilizer application by 74.3 kilograms per hectare; and imported feed (mainly concentrates) by 13.4 kilograms of dry matter per hectare in order to achieve environmental efficiency. The adjustments that would be required if environmentally inefficient farms were to adopt best practice technology and move towards their environmental production frontiers indicate that the production of pollutants (nitrogen surplus) could be reduced at negligible cost to milk production. The positive correlation between technical and environmental efficiencies indicates that improving environmental efficiency could be associated with improvements in technical efficiency. Thus, policies aimed at improving efficiency, such as educating farmers in best practice technology, could have substantial rewards. The results for slacks in the DEA environmental analysis (Chapter 9) indicated that considerable improvements in environmental efficiency can be achieved at no output loss. That is, environmental efficiency can be improved without sacrificing technical efficiency.

10.9 Policy recommendation

Before any further recommendations can be made, a declaration of the limitations of the findings and conclusions is warranted. Firstly, the data used was financial information of 37 farms and the data were not collected specifically for the analysis of efficiency but for routine management advice by Tammac Consulting. The decision to use the dataset was a case of making the best out of the available data. Much more information could have been included had the data been specifically collected for the purposes of the study. Secondly, the data relates to a small geographical part of South Africa, thus any inference beyond the sample should be done with care. A suggestion to remedy the limitation brought about by the locality of the data would be to conduct a similar study at a national level which would include more farms thus rendering the findings more reliable. However, salient findings were obtained from the available data as was reported in various empirical chapters and conclusions.

The findings of the modelling of efficiency, technical efficiency and environmental efficiency have been discussed at length and the attendant conclusions have been made. What remains is drawing policy recommendations and suggestions for further research on the efficiency of the dairy industry in South Africa. The analyses that were performed in this dissertation were complicated due to the dataset used being restrictive and limited. This leads to the first recommendation pertaining to keeping proper records in the dairy industry in South Africa. It is recommended that the state (Department of Agriculture, Forestry and Fisheries, DAFF) should have annual surveys with the intentions of quantifying inputs and outputs of environmentally-detrimental inputs such as nitrogen. These surveys should also be geo-referenced as much as possible to enable researchers and policy-makers to pin-point areas of potential environmental nitrate leaching problems. Much work has already been done in KwaZulu-Natal to map the soils with their properties and this information could help in identifying soils with high leaching potentials.

Given that many small dairy farms operate near the margin of viability, enhanced revenues from higher product prices, reduced cost of production, or value-added activities such as agri-tourism or cheese-making may help in sustaining these operations. A more tailor-made approach to management could be an appealing option for improving the viability of the small dairy farms. For example, some small farms may be able to adopt production technologies, such as better managed grazing, that lead to lower gross returns, but substantially lower costs. Others have turned to organic production, which offers higher milk prices (along with higher feed costs). Regardless of the survival methods adopted by small dairy farms, continued shifts of production to larger enterprises will place downward pressure on conventional milk production costs and prices, and that will impose powerful competitive pressures on small farms and on alternative products and production technologies. Farmers' incomes can also be enhanced if farmers could demonstrate environmental benignity thus market their products as being environmentally friendly (such initiatives are already paying dividends in the wine industry in the Western Cape under the Biodiversity Initiative).

Further models for analysing environmental efficiency were presented, albeit mostly being adaptations and modifications of existing methodologies. Although environmental degradation through pollution has not been measured and declared a problem, the study suggests that being proactive would be beneficial to the dairy industry in this regard. Being proactive would imply dairy farms being more conscious of how they use polluting inputs in the production process. An interesting revelation in environmental efficiency analysis was that technical efficiency and environmental efficiency are independent of each other, although not mutually exclusive. The implication is that farmers can reduce the use of their polluting inputs, nitrogen in this case, without sacrificing either technical efficiency and/or production as this was indicated by the fertiliser and other nitrogen related slacks in Chapter 9.

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